ESSAYS ON ENDOGENOUS TECHNOLOGICAL CHANGE AND INTERNATIONAL R&D SPILLOVERS

By

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To the Memory of My Father

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TABLE OF CONTENTS

Page

ACKNOWLEGDEMENTS iv

ABSTRACT viii

CHAPTERS

1 INTRODUCTION 1

2 ENDOGENOUS TECHNOLOGICAL CHANGE IN A HETEROGENEOUS SOCIETY 11

Review of Literature 11
Description of the Model 13
    A Heterogeneous Society 13
    Endogenous Technological Change 14
Discussion of the Model 18
    Distribution Effects 18
    An Integrating World 22
Future Extension of the Model 27
Summary 29

3 INTERNATIONAL R&D SPILLOVERS 32

Review of Literature 32
The Model 36
    Basic Specification 36
    Extensions of the Basic Specification 39
Data 40
Results 42
    Spillovers through CGM: Basic Specification 42
    Spillovers through CGM: Extended Specifications 53
    Spillovers through FDI 53
    Simultaneous Channels of Spillovers 54
Summary 55

4 INTERNATIONAL AND INTERSECTORAL R&D SPILLOVERS 57

Review of Literature 57
The Model 60
  TFP and Spillovers 60
  Wages and Spillovers 63
Data 64
Results 76
  The Effects of R&D Spillovers on TFP 76
  The Effects of R&D Spillovers on Wages 77
Summary 83

5 CONCLUSIONS 85

APPENDICES

A DERIVATION AND CALIBRATION FOR ENDOGENOUS TECHNOLOGICAL CHANGE IN A HETEROGENEOUS SOCIETY 88

The Balanced Growth Path 88
The National Income Accounts 92
How Heterogeneous a Society Can Be? 96

B DATA DESCRIPTION FOR INTERNATIONAL R&D SPILLOVERS 101

C DATA DESCRIPTION FOR INTERNATIONAL AND INTERSECTORAL R&D SPILLOVERS 103

The Source of Data 103
The Construction of Variables 104
  Total Factor Productivity 104
  Wages and Capital Stock per Worker 105
  R&D Stock 106
  R&D Spillovers 106

REFERENCES 109

BIOGRAPHICAL SKETCH 113

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The main body of this dissertation consists of three parts. In chapter 2, I recast the Romer model of endogenous technological change in a heterogeneous society where human capital is distributed unequally among the population and is allocated jointly with labor between R&D and manufacturing. In addition to the conventional scale effects, my model has the new distribution effects. Given the result of my calibration that there is great inequality in human capital endowment, the distribution effects explain the real world quite well. However, the relevant unit of observation is neither any sovereign nation nor the whole world, but rather an integrated subworld.

Chapter 3 investigates the roles of trade and foreign direct investment (FDI) in R&D spillovers among industrialized countries. I find that total factor productivity (TFP) of a country is enhanced significantly by R&D activities of other countries through the channel of capital goods trade. My estimation shows that more than one third of the

benefits of R&D investment in a typical Group-Seven country accrue to its trade partners within the OECD. Although no correlation is found between TFP and a measure of foreign R&D embodied in FDI, a significant correlation is found between TFP and the intensity of FDI. In addition, I obtain results suggesting the importance of absorptive capacity to international R&D spillovers.

In chapter 4, I extend my empirical investigation of international R&D spillovers down to the sectoral level. I find that, in addition to domestic own-sector R&D stock, domestic cross-sector R&D spillovers and foreign R&D spillovers embodied in flows of capital goods have positive effects on wages. Experiments with control variables such as physical capital per worker and time effects show that the positive effects of spillovers on wages are robust. However, domestic cross-sector R&D spillovers and foreign R&D spillovers are so highly correlated to each other that their individual effects cannot be separated. How to isolate these two spillovers empirically is an important topic for future research.

CHAPTER 1
INTRODUCTION

The bulk of productive economic activities fall into two mutually exclusive categories:[1] goods-producing activities and knowledge-producing activities. Goods production and knowledge production are distinct from each other by their outputs. Goods are usually rivalrous and excludable, while knowledge is nonrivalrous but can be excludable, nonexcludable, or somewhere between the two extremes.

Moreover, these two kinds of activities are distinct from each other by their inputs, especially their human inputs. Goods production is labor intensive, requiring the ability to do something routine and some other low skills. In contrast, knowledge production is human capital[2] intensive, requiring the ability to do something original and some other high skills. Therefore, the production possibility frontier in the space of goods and knowledge is concave even if the production function of goods and that of knowledge are assumed to be identical with respect to all nonhuman inputs.

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[1] Of course, joint production of goods and knowledge, such as learning by doing, does exist in the reality. However, such joint production is dominated by separate production, at least in modern industrialized nations.

[2] The usage of "human capital" here follows Romer (1990) though there is no "human capital" accumulation in either the Romer model or ours. There are potentially many alternative names for the ability to produce knowledge, such as entrepreneurship (Baumol, 1990), talent (Murphy, Shleifer, and Vishny, 1991), and symbolic-analytic skill (Reich, 1991).

Although human capital and labor are usually demanded separately, they are always supplied jointly. Therefore, when an individual is employed in the goods-producing sector, her ability to produce goods is utilized while her ability to produce knowledge is wasted. When earning her wage in an assembly line, a worker is forsaking the opportunity of getting paid as an inventor working in an R&D lab. Conversely, the opportunity cost of inventing new ideas is the wage that could be earned otherwise with unused labor.

The ability to produce goods is distributed fairly uniformly among the population. However, the variance in the ability to produce knowledge is enormous.[3] Hence, while the opportunity cost of producing knowledge is too frivolous for some to care, it is too onerous for others to bear. Consequently, for the majority of the population, the two occupations are not perfect substitutes. The joint allocation of human capital and labor between goods production and knowledge production is the collective outcome of occupational choices made by a heterogeneous population based on economic incentives.

The above paragraphs have described some essential features of modern industrialized societies, but some of them are still missing in existing endogenous growth models, such as Aghion and Howitt (1992), Grossman and Helpman (1991), Romer (1990), and Segerstrom, Anant, and Dinopoulos (1990).

Take the endogenous technological change model of Romer (1990) as an example. In the Romer model, separated from a manufacturing sector, an R&D sector produces designs that are nonrivalrous, excludable in their uses in goods production, but nonexcludable in their uses in knowledge production. It is this partial excludability that provides economic incentives for private knowledge production on one hand and channels for knowledge spillovers on the other.

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[3] Although it is impossible for anyone to be ten times as productive as her colleagues in an assembly line, it seems no problem for some of us to be so in an R&D lab. For example, Thomas Edison, America's most productive inventor in the golden age of independent inventors, had a lifetime output of 1093 patents, leaving even Elmer Sperry, the silver medallist of his time with more than two hundred patents, in the dust.

However, Romer models labor and human capital as neither separately demanded nor jointly supplied. Not without apology, he chooses a formulation that "neglects the fact that L (labor) and H (human capital) are supplied jointly" (p.S85, parentheses are added by this author); and he is consequently compelled to "imagine that there are some skilled persons who specialize in human capital accumulation and supply no labor" (p.S85) to excuse an annoying characteristic of his model that all labor is engaged in goods production while all human capital is allocated between the goods-producing sector and the knowledge-producing sector.[4]

Furthermore, Romer does not incorporate heterogeneity in human capital endowment into his model. Hence, "any person can devote human capital to either the final-output sector or the research sector" (p.S85), and the incentives to specialize in the production of knowledge, which have brought forth such great inventors as Thomas Edison, Elmer Sperry, Edwin Land, and Jerome Lemelson for America, are missing.

As a matter of fact, the assumption of a homogeneous society populated by identical individuals, or "representative agents" in our profession's jargon, is a hallmark of all existing two-sector endogenous growth models. In such a homogeneous society, every morning at equilibrium, identical residents randomly walk into either an R&D lab or an assembly line. They fill the economy like gas molecules fill an enclosed chamber. All have the same probability to be located at any particular place but their whereabouts at any particular point in time are completely decided by chance. Obviously, this is an oversimplified picture of the real world.

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[4] With only one kind of human resource allocated between sectors, it makes little sense to have more than one in the first place. Hence, when adopting Romer's framework, researchers usually choose to keep only "labor" in their models.

Oversimplification has rendered existing endogenous growth models not only theoretically flawed but also empirically challenged. Jones (1995a, 1995b) cites a six-fold explosion in the number of scientists and engineers engaged in formal R&D in the United States between 1950 and 1988 versus a nearly constant growth rate of total factor productivity (TFP) during the same period as evidence against the "scale effects" prediction of two-sector endogenous growth models.

In his attempt to reconcile the theory and the reality, Jones modifies the Romer model to eliminate scale effects. Although growth in the modified model is generated endogenously through R&D, a positive long-run growth rate in per capita income exists only if there is a positive rate of population growth.

In chapter 2 of this dissertation, we also seek the reconciliation of the theory and the reality, but in a new direction. Instead of eliminating scale effects, we introduce "distribution effects" by recasting the endogenous technological change model of Romer (1990) in a heterogeneous society where human capital is distributed unequally among the population and is allocated jointly with labor between R&D and manufacturing.

The derivation of the balanced growth path and the national income accounts is provided in Appendix A. Appendix A also includes the calibration of the degree of inequality in human capital endowment based on observed income differentials and the manufacturing share of employment.

In our heterogeneous growth model of chapter 2, investment in R&D aimed at economic gains from ensuing technological change fuels the engine of productivity growth. Because of the nonrivalrous nature of technology, one country's R&D efforts may power not only its own economic growth but others' as well. Without international R&D spillovers, it is impossible to explain the phenomenon that some small and historically backward economies with Lilliputian investment in R&D have succeeded in closing the gap in standard of living with the world's technological giants who invest prodigiously in the creation of new technology.

However, knowledge does not flow spontaneously. While some of them have made their miracles of catching-up by tapping the exuberance of modern technology, the majority of the world's small and poor have evidently failed in seizing the economic opportunities created by technological advancement. Although theoretical models have identified some probable channels of international R&D spillovers and some factors that may affect the flows of ideas along these channels, they are incapable of either verifying the existence, or evaluating the importance, of these channels in the real world. Therefore, empirical inquiries into international R&D spillovers are of both theoretical and practical significance.

Empirical study of international R&D spillovers is a challenging intellectual enterprise. First, how to measure knowledge?[5] Since the output of the knowledge-producing sector is notoriously measurement-resistant, most of researchers choose to proxy the value of R&D output with the value of R&D input, and this solution seems to be theoretically justified. In endogenous growth models with horizontally differentiated intermediate inputs designed by an R&D sector of constant returns, the stock of knowledge (that is, the number of designs) is proportional to the accumulation of resources devoted to R&D activities.

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[5] See Griliches (1979, 1988) for a discussion on the measurement of R&D output.

How to measure the international flow of knowledge poses an even more formidable problem. Guided by past experience in firm- and industry-level studies,[6] empiricists of international R&D spillovers have been exploring three different trails: the externality approach, the distance approach, and the flow approach. The externality approach is a straightforward extension of externalities from the microeconomic level to the macroeconomic level, in which foreign R&D stock enters the domestic production function in a way symmetric (except with some lag) to domestic R&D stock (Bernstein and Mohnen, 1997; Bernstein and Yan, 1997). Unfortunately, the applicability of the externality approach is limited by the problem of identification. Not only is this approach invalid for any group of more than a few countries, but also it is invalid for any group of countries among which the economic and technological ties are not so predominant that the group can be analyzed in isolation from the rest of the world.

The distance approach, or the "pipe" approach, is based on the analogy that there may be some magnitudes which restrict the flow of knowledge in much the same way that the physical dimensions, such as the length and caliber, of a pipe limit the flow of water. In fact, several suspects such as openness[7] (an analogue to caliber), geographic distance, technical distance, or language dissimilarity (analogues to length), or some combinations of them have been tried and, in the majority of cases, convicted empirically (Eaton and Kortum, 1996; Park, 1995; Sjöholm, 1996).

However, these endeavors come short of generating rich policy implication. For example, if more openness is related to more R&D spillovers and hence faster growth, does more openness mean more foreign direct investment (FDI) or more trade? And, if more trade, more trade in what? Besides, the government can do little if anything about physical or nonphysical distances.

The rationale of the flow approach is that knowledge may be "embodied" in something physical like goods, capital, patents, and individuals; and we may, therefore, be able to measure the flow of knowledge indirectly by measuring the flow of knowledge "carriers". This approach promises the possibility of identifying major channels of R&D spillovers, evaluating their relative importance, and providing explicit guidelines for policy making.[8]

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[6] See Griliches (1992) and Nadiri (1993) for a survey on issues raised by the attempt to measure R&D spillovers.

[7] How to measure "openness" may be an equally controversial issue as how to measure "spillovers." In fact, researchers either avoid the term openness by talking about international trade instead, or proxy openness with some measure related with international trade. This is equivalent to acknowledging that spillovers are embodied in traded goods.

[8] Another reason why the flow approach may be superior to the distance approach is that flows are asymmetric by definition (That is why we always have both inflows and outflows.), but distance is a concept subject to the restriction of symmetry. Hence, the distance approach may understate spillovers in one direction while overstate spillovers in the other.

The first attempt to empirically investigate international R&D spillovers is made by Coe and Helpman (1995) using the flow approach. Using a sample of 21 OECD countries plus Israel, Coe and Helpman examine the extent to which new technology diffuses between industrialized nations through the particular conduit of international trade.

However, there are several puzzles about the results obtained by Coe and Helpman. First, they estimate that the own rate of return on R&D investment in a typical Group-Seven (G7) country is about 120 percent. This is not consistent with various single-country, firm- and industry-level studies, which indicate that rates of return to R&D in G7 countries typically lie in a range between 20 and 40 percent (Nadiri, 1993, pp.10-12). Second, their estimation ranks Japan the second smallest among the 21 countries in the elasticity of TFP with respect to R&D capital of the United States, which contradicts the common belief that Japan is among the top beneficiaries of R&D spillovers from the United States.

Our first goal in chapter 3 is to extend Coe and Helpman's study of international R&D spillovers to trade in capital goods. Since formal theories of technological change usually model new technology as embodied in new capital goods instead of goods in general, we expect that by using capital goods as the spillover carrier and by adopting a new empirical specification, we may solve the Cole-Helpman puzzles. Of course, some might argue that knowledge is embodied in noncapital goods as well in the reality. Nevertheless, on average, the content of technology embodied in noncapital goods, raw materials in particular, is considerably lower than in capital goods. Others might argue that trade in capital goods is a major component of international trade. However, the composition of bilateral trade is highly volatile both across trade partners and over extended periods of time. Albeit statistically measured with a reasonable accuracy, trade in goods may be a distorted gauge of international R&D spillovers.

As complements to formal theories which treat technology as "blueprints" or "designs" that are readily accessible through market transactions, the so-called appreciative theories emphasize that technology is partially organizationally embedded, tacit, and cumulative and describe R&D spillovers as complex processes involving various sorts of personal contacts motivated by economic incentives. From this perspective, multinational enterprises (MNEs), the most internationalized economic organizations, may be important technological bridges between nations. As these transnational firms expand their operations through FDI, not only capital goods but also their incorporeal capital, their expertise and their trade secrets flow into the host country,[9] not only business facilities but also direct personal contacts are established. Hence, our second mission in chapter 3 is to extend Coe and Helpman's study to inward FDI.

In chapter 3, we also investigate the role of absorptive capacity in international R&D spillovers. Previous firm-level studies such as Cohen and Levinthal (1989) have found that R&D not only generates knowledge but also enhances the ability to absorb knowledge. This consideration has not been incorporated in empirical studies of international R&D spillovers.

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[9] It is the knowledge embodied in secret gadgets, managerial and marketing know-how, and so on, that provide advantages to counter disadvantages related with unfamiliarity in competing with local companies that also enjoy access to traded capital goods.

Most of the data used in chapter 3 come from Coe and Helpman (1995). The description of the data is provided in Appendix B.

The success in empirical studies of international R&D spillovers at the aggregate level naturally leads to new adventures at the sectoral level. Keller (1997) studies simultaneous international and intersectoral R&D spillovers using the flow approach based on a sample of thirteen manufacturing industries in eight OECD countries over the period 1970-1991. To model the cross-sector R&D spillovers, he uses country- and time-invariant input-output tables of domestic and imported intermediate goods. As an alternative, he also uses the patent input-output table constructed by Evenson, Putnam, and Kortum (1991) based on Canadian patent data. His results not only confirm the earlier findings at the aggregate level that there are significant international R&D spillovers but also indicate the existence of intersectoral R&D spillovers.

In chapter 4, we extend our empirical investigation of international R&D spillovers to simultaneous international and intersectoral R&D spillovers. We depart from the existing literature in several important respects. First, we use country- and time-specific input-output tables of capital formation while the existing literature uses country- and time-invariant input-output tables of intermediate goods. Second, since TFP measures tend to be error-ridden at the sectoral level, we also investigate the impact of R&D spillovers on the average real wage, which is closely linked to productivity. Third, since our sample includes total services, our study covers about 80 percent of a typical developed economy.

Our empirical investigation at the sectoral level is based on massive data construction work. The description of the data is provided in Appendix C.

CHAPTER 2
ENDOGENOUS TECHNOLOGICAL CHANGE IN A HETEROGENEOUS SOCIETY

Review of Literature

Existing R&D-based models of economic growth (Aghion and Howitt, 1992; Grossman and Helpman, 1991; Romer, 1990; Segerstrom, Anant, and Dinopoulos, 1990) have underscored the fact that the engine of economic growth is technological change, and the fuel of technological change is human capital. Unfortunately, they have overlooked the fact that the distribution of human capital is very uneven among a population.

Of course, a population is heterogeneous in many other dimensions. Nonetheless, it is heterogeneity in human capital endowment that is essential. This is so not only because heterogeneity in human capital endowment is of great magnitude but also because it is the source of heterogeneity in many other individual characteristics, such as income, consumption, savings, and even political views.

However, the introduction of heterogeneity in human capital endowment into endogenous growth models is a new enterprise with many unknowns. One major problem is how to model heterogeneity mathematically so that the new model is tractable. Another major problem is how to measure heterogeneity empirically. At least partly because of these difficulties, growth theorists have generally kept heterogeneity out of their models.

This seemingly innocuous neglect has rendered these models not only theoretically flawed but also empirically challenged.

Jones (1995a, 1995b) cites a six-fold explosion in the number of scientists and engineers engaged in formal R&D in the United States between 1950 and 1988 versus a nearly constant TFP growth during the same period as evidence against the "scale effects" prediction of two-sector endogenous growth models. To reconcile the theory and the reality, Jones modifies the Romer model to eliminate scale effects. Although growth in the modified model is generated endogenously through R&D, a positive long-run growth rate in per capita output exists only if there is a positive rate of population growth.

We also seek the reconciliation of the theory and the reality, but in a new direction. Instead of eliminating scale effects, we introduce *distribution effects* by recasting the Romer model in a heterogeneous society where human capital is distributed unequally among the population and is allocated jointly with labor between R&D and manufacturing.

Based on observed income differentials and the manufacturing share of employment, calibration shows that the inequality in human capital endowment is of phenomenal magnitudes. This high degree of heterogeneity implies that distribution effects are different from scale effects.

With distribution effects, our new heterogeneous vintage of R&D-based models of economic growth is capable of explaining most of the stylized facts. But the relevant unit of observation is neither any sovereign nation nor the whole world, but rather an integrated subworld. When the integrated subworld expands to incorporate developing economies, it absorbs human capital and labor in proportions more uneven than its own and thus becomes more heterogeneous. As a result, wage differentials increase, workers switch from manufacturing to R&D at the margin, but the growth rate may rise only moderately. In addition, since wage rates are the same in the integrated subworld, countries converge, conditional on the human capital endowment of their population.

The layout of the rest of the chapter is as follows. First, we will recast the endogenous technological change model of Romer (1990) in a heterogeneous society. Next, we will derive the comparative statics and show how distribution effects and unbalanced integration explains the real world. Then, we will discuss topics of future research. And last, we will conclude the chapter with a brief summary. We leave the derivation of the balanced growth path and national income accounts as well as the calibration of the degree of heterogeneity in the real world to Appendix A.

Description of the Model[1]

A Heterogeneous Society

Consider a society populated by a continuum of infinitely lived workers indexed by the variable $z \in [0, L]$. Workers are identical in all respects except in their human capital endowment. Let the society's aggregate labor endowment be L so that each worker's labor endowment is one unit. Let the society's aggregate human capital endowment be H so that the average human capital endowment is H/L. Like Romer, we assume that both L and H are constant and are inelastically supplied. Unlike Romer, however, we assume that individual z's human capital endowment is

$$h(z) = \frac{\mu H}{L}\left(\frac{z}{L}\right)^{\mu-1} \tag{1}$$

where $\mu \in [1, \infty)$ is *the distribution parameter* characterizing the degree of inequality in human capital endowment. The larger μ is, the more unequal human capital is distributed among the population, and more heterogeneous the society is. Note that the human capital endowment of individual L, the most talented, is

$$h(L) = \mu H/L. \tag{2}$$

Hence, the most talented is endowed with μ times as much human capital as the average member of the society, and she is, therefore, μ times as efficient as the average person in knowledge production.

Although hypothetical, our heterogeneous society is simple and flexible. It has only one additional parameter that gives a straightforward measure of the degree of heterogeneity, and it encompasses two important special cases: a homogeneous society ($\mu = 1$) and a heterogeneous society with its population uniformly distributed with respect to human capital endowment ($\mu = 2$).

Endogenous Technological Change

Following Romer (1990), we postulate an economy of three sectors: a competitive final goods sector, a monopolistic intermediate inputs sector,[2] and a competitive R&D

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[1] Since we will concentrate on the balanced growth path, the time argument of all variables will be omitted for notational convenience whenever no confusion will be caused.

[2] The separation of intermediate goods from final goods is convenient but not necessary. Rivera-Batiz and Romer (1991) provide an alternative description of the same model without such separation.

sector. The final (consumption/capital) good is the numeraire and is produced using labor and a continuum of differentiated intermediate inputs indexed by the variable *i*,

$$Y = L_Y^{\alpha} \int_0^A x(i)^{1-\alpha}\, di \tag{3}$$

where L_Y is labor engaged in final goods production, α is the labor share of final goods output,[3] A is the index of the most recently invented type of intermediate, and $x(i)$ is the aggregate stock of intermediate of type *i*.

Note that we explicitly depart from Romer in assuming that only a part of labor (L_Y) is allocated to final goods production. Note also that we *implicitly* depart from Romer in assuming that a part of human capital (H_Y) is allocated jointly with labor to final goods production but neither makes a contribution to, nor receives compensations from, the final goods sector.

Taking the prices of intermediates ($p(i)$ for the *i*th intermediate) and the wage rate of labor w_L as given, the producers of final goods choose the quantity of labor and the quantities of intermediates to maximize their profits

$$\int_0^A \left[L_Y^{\alpha} x(i)^{1-\alpha} - p(i)x(i) \right] di - w_L L_Y . \tag{4}$$

The intermediate sector is composed of an infinite number of firms on the interval [0, *A*] which *effortlessly* transform capital goods into intermediates one for one. Taking the demand for the *i*th intermediate $p(i)$ and rate of return r as given, the firm that has purchased

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[3] It can be shown that the labor share of national income is

$$\alpha^* = \frac{\alpha r + g\alpha(1-\alpha)}{r + g\alpha(1-\alpha)}$$

from the R&D sector the monopoly right of producing intermediate *i* chooses a level of output to maximize its revenue minus variable cost

$$\pi(i) = p(i)x(i) - rx(i). \tag{5}$$

The R&D sector uses existing designs and human capital as inputs to produce designs for new types of intermediates according to the following production function[4]

$$\dot{A} = \delta A H_A \tag{6}$$

where $\dot{A}$ is the output of new designs, δ is a parameter of research productivity, and H_A is human capital devoted to invention.

Although equation (6) is exactly the same in appearance as its counterpart in Romer (1990), we implicitly depart from Romer in assuming that a part of labor (L_A) is allocated jointly with human capital to knowledge production but neither makes a contribution to, nor receives compensations from, the R&D sector.

Taking the price of designs P_A and the wage rate of human capital w_H as given, the R&D sector maximizes its profits

$$P_A \delta A H_A - w_H H_A. \tag{7}$$

Taking the price of designs P_A, the rate of return *r*, the wage rate of labor w_L, and the wage rate of human capital w_H as given, individual *z* chooses her consumption *c*(*z*,*t*),

---

where *g* is the balanced growth rate and *r* is the equilibrium rate of return. However, for *g* and *r* of reasonable magnitudes, α is only slightly smaller than α^*.

[4] As Jones (1995a) points out, this specification is somewhat arbitrary. It is adopted here to facilitate comparison with the Romer model. Also see Eicher and Turnovsky (1996) for a discussion on the general specification of growth models.

investment in capital $\dot{k}(z,t)$, investment in designs $P_A(t)\dot{a}(z,t)$, and *occupation* to maximize her lifetime utility

$$U(z) = \int_0^\infty \frac{c(z,t)^{1-\sigma} - 1}{1-\sigma} e^{-\rho t} dt \tag{8}$$

subject to her dynamic budget constraint[5]

$$\dot{k}(z,t) + P_A(t)\dot{a}(z,t) + c(z,t) = r(t)k(z,t) + r(t)P_A(t)a(z,t) + w(z,t) \tag{9}$$

where $r(t)k(z,t)$ and $r(t)P_A(t)a(z,t)$ are her returns on capital and returns on designs respectively, $w(z,t)$ is her wage income which is either w_L if she chooses to work in the manufacturing sector or $w_H h(z)$ if she chooses to work in the R&D sector, σ is the inverse of the elasticity of intertemporal substitution, and ρ is the subjective discount rate.

As shown in Appendix A, the balanced growth rate is

$$g = \frac{\mu(1-\alpha)\delta H - \rho}{\mu(1-\alpha)+\sigma}. \tag{10}$$

The manufacturing share of human capital, is

$$\frac{H_Y}{H} = \frac{\sigma + \frac{\rho}{\delta H}}{\mu(1-\alpha)+\sigma}. \tag{11}$$

The manufacturing share of employment, is

---

[5] Along the balanced growth path, all shares are constant by definition. For this reason, individuals' investment in capital, returns on capital, investment in designs, returns on designs, and consumption are all proportional to their wage income. In other words, although individuals are different in the *level* of their income and expenditure, they are identical in the *composition* of their income and expenditure. For the same reason, there is no room for lending and borrowing.

$$\frac{L_Y}{L} = \left[\frac{\sigma + \dfrac{\rho}{\delta H}}{\mu(1-\alpha)+\sigma} \right]^{\frac{1}{\mu}} . \tag{12}$$

Income inequality can be measured by the equilibrium ratio of the wage earned by the most talented inventor to the wage earned by all laborers and the marginal inventor. We call this the wage limits ratio, and it is given by

$$\frac{w(L)}{w(L_Y)} = \frac{w_H h(L)}{w_L} = \frac{w_H h(L)}{w_H h(L_Y)} = \left(\frac{L_Y}{L}\right)^{1-\mu} = \left[\frac{\sigma + \dfrac{\rho}{\delta H}}{\mu(1-\alpha)+\sigma} \right]^{\frac{1-\mu}{\mu}} . \tag{13}$$

An alternative measure of the wage differential is the equilibrium ratio of the average inventor wage to the (average) laborer wage. We call this the wage averages ratio, and it is given by

$$\frac{w_H H_A}{w_L L_A} = \left(\frac{w_H H_A}{w_L L_Y}\right) \left[\left(\frac{L_Y}{L}\right)^{-1} - 1 \right]^{-1} =$$

$$\frac{\mu(1-\alpha)\delta H - \rho}{\mu(\sigma\delta H + \rho)} \left\{ \left[\frac{\sigma + \dfrac{\rho}{\delta H}}{\mu(1-\alpha)+\sigma} \right]^{-\frac{1}{\mu}} - 1 \right\}^{-1} . \tag{14}$$

Discussion of the Model

Distribution Effects

In the following comparative statics, we will concentrate on changes in the three most important demographic characteristics: *L*, *H*, and μ. Moreover, changes in *L*, *H*, and μ will be in percentage terms so that their effects can be compared quantitatively. Taking the partial derivatives of (10)-(14) with respect to L and multiplying the results by L, we have

$$L\frac{\partial g}{\partial L} = L\frac{\partial}{\partial L}\left(\frac{H_Y}{H}\right) = L\frac{\partial}{\partial L}\left(\frac{L_Y}{L}\right) = L\frac{\partial}{\partial L}\left[\frac{w(L)}{w(L_Y)}\right] = L\frac{\partial}{\partial L}\left(\frac{w_H H_A}{w_L L_A}\right) = 0. \quad (15)$$

When L increases, holding H and μ constant, there will be a decrease in the quality of the population counterbalancing the increase in the quantity of the population. Hence, the growth rate, employment shares, and wage ratios all remain the same.

Taking the partial derivatives of (10)-(14) with respect to H and multiplying the results by H, we have *scale effects*

$$H\frac{\partial g}{\partial H} = \frac{\mu(1-\alpha)\delta H}{\mu(1-\alpha)+\sigma} > 0, \quad (16)$$

$$H\frac{\partial}{\partial H}\left(\frac{H_Y}{H}\right) = -\frac{\rho}{\delta H[\mu(1-\alpha)+\sigma]} < 0, \quad (17)$$

$$H\frac{\partial}{\partial H}\left(\frac{L_Y}{L}\right) = -\frac{\rho}{\mu(\sigma\delta H+\rho)}\left(\frac{L_Y}{L}\right) < 0, \quad (18)$$

$$H\frac{\partial}{\partial H}\left[\frac{w(L)}{w(L_Y)}\right] = -\frac{(1-\mu)\rho}{\mu(\sigma\delta H+\rho)}\left(\frac{L_Y}{L}\right)^{1-\mu} > 0, \quad (19)$$

$$H\frac{\partial}{\partial H}\left(\frac{w_H H_A}{w_L L_A}\right) =$$

$$\frac{\mu\delta H\rho[\mu(1-\alpha)+\sigma]\left[\left(\frac{L_Y}{L}\right)^{-1}-1\right] - \rho[\mu(1-\alpha)\delta H-\rho]\left(\frac{L_Y}{L}\right)^{-1}}{\mu^2(\sigma\delta H+\rho)^2\left[\left(\frac{L_Y}{L}\right)^{-1}-1\right]^2} >< 0. \quad (20)$$

When H increases, holding L and μ constant, there will be an increase in $h(z)$ for all $z\in(0, L]$ but this increase will be disproportionate according to (1). With increased human capital endowment, the most talented laborers will be better off by switching from manufacturing to R&D. Hence, the R&D share of employment will increase [(18)] and the manufacturing share of human capital will decrease [(17)]. The growth rate rises [(16)] not only because of the increase in the quantity of R&D employment at the margin but also because of the increase in the quality of R&D employment within the margin. However, the wage difference between the most talented inventor and the least talented inventor widens [(19)]. The sign of (20) is indeterminate because of the existence of two opposing effects. According to (14), $w_H H_A/w_L L_A$ can be decomposed into two parts and the increase in H causes one part, $w_H H_A/w_L L_Y$, to rise but causes the other, $[(L_Y/L)^{-1}-1]^{-1}$, to fall.

Taking the partial derivatives of (10)-(14) with respect to μ and multiplying the results by μ, we have *distribution effects*[6]

$$\mu\frac{\partial g}{\partial\mu}=\frac{\mu(1-\alpha)(\sigma\delta H+\rho)}{[\mu(1-\alpha)+\sigma]^2}>0, \tag{21}$$

$$\mu\frac{\partial}{\partial\mu}\left(\frac{H_Y}{H}\right)=-\frac{\mu(1-\alpha)(\sigma\delta H+\rho)}{\delta H[\mu(1-\alpha)+\sigma]^2}<0, \tag{22}$$

$$\mu\frac{\partial}{\partial\mu}\left(\frac{L_Y}{L}\right)=-\left[\frac{1-\alpha}{\mu(1-\alpha)+\sigma}+\ln\left(\frac{L_Y}{L}\right)\right]\left(\frac{L_Y}{L}\right)>0,^{7} \tag{23}$$

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[6] We can plot (10) in the space of H and g in the same way as Romer (1990)'s figure 2. As μ becomes larger, not only the slope of the graph becomes more close to 1 from below, but also the horizontal intercept of the graph becomes more close to 0 from above. Hence, the more heterogeneous a society is, the less human capital is necessary for it to escape the trap of stagnation.

$$\mu\frac{\partial}{\partial\mu}\left[\frac{w(L)}{w(L_Y)}\right]=-\left[\frac{(1-\mu)(1-\alpha)}{\mu(1-\alpha)+\sigma}+\ln\left(\frac{L_Y}{L}\right)\right]\left(\frac{L_Y}{L}\right)^{1-\mu}>0, \tag{24}$$

$$\mu\frac{\partial}{\partial\mu}\left(\frac{w_H H_A}{w_L L_A}\right)=$$

$$\frac{\rho\left[\left(\frac{L_Y}{L}\right)^{-1}-1\right]-\left[\mu(1-\alpha)\delta H-\rho\right]\left[\frac{1-\alpha}{\mu(1-\alpha)+\sigma}+\ln\left(\frac{L_Y}{L}\right)\right]\left(\frac{L_Y}{L}\right)^{-1}}{\mu(\sigma\delta H+\rho)\left[\left(\frac{L_Y}{L}\right)^{-1}-1\right]^2}>0. \tag{25}$$

When μ increases, holding L and H constant, there will be an increase in $h(z)$ for all $z\in(Le^{-1/\mu}, L]$. However, this increase is unevenly distributed, and it is also at the expense of a decrease in $h(z)$ for all $z\in(0, Le^{-1/\mu})$. With decreased human capital endowment, the least talented inventors will be better off by switching from R&D to manufacturing. Hence, not only will less human capital be wasted in goods production [(22)], but also less labor will be wasted in knowledge production [(23)]. Since the society becomes more efficient in allocating human resources, it will grow faster [(21)]. However, the two ends of its income spectrum become further apart [(24)] because the most talented possesses even more human capital. According to (14), the wage averages ratio $w_H H_A/w_L L_A$ rises [(25)] because the increase in μ causes both $w_H H_A/w_L L_Y$ and $[(L_Y/L)^{-1}-1]^{-1}$ to rise.

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[7] Solving $\ln\left(\frac{L_Y}{L}\right)=\frac{1}{1-\mu}\ln\left[\frac{w(L)}{w(L_Y)}\right]$ from (A46), substituting it into the brackets, and rearranging, we can express the content of the original brackets as $\frac{1-\alpha}{(\mu-1)[\mu(1-\alpha)+\sigma]}$ $\left\{\mu-1-\mu\ln\left[\frac{w(L)}{w(L_Y)}\right]-\frac{\sigma}{1-\alpha}\ln\left[\frac{w(L)}{w(L_Y)}\right]\right\}$. Since $\sigma > 0$ and $\ln\left[\frac{w(L)}{w(L_Y)}\right]>1$, the original brackets is negative and thus (23) is positive.

A comparison of (16) and (21) reveals that the distribution effect on growth rate can be far smaller than the scale effect (about 1 versus 100) if μ is as large as those calibrated in table A-2 of Appendix A.

An Integrating World

We examine the effects of integrating one society with another. Two simple cases are considered. The first is the case of balanced integration in which the original society is joined by a small new part whose work force's composition is the same. Hence, heterogeneity is not affected, but human capital and labor rise proportionately. Consequently, in the integrated society, the growth rate is higher, a bigger share of human capital is devoted to R&D, a smaller share of labor is devoted to manufacturing, and income is distributed more unequally. This is similar to the case of scale effects.

The second is the case of perfectly unbalanced integration in which the original society is joined by a small new part whose workers have no human capital at all. The increase in labor supply raises the demand for intermediates, monopolist profits, the price of designs, and the wage rate of inventors, inducing the most talented laborers to switch job. As shown in table A-2 of Appendix A, however, if μ is large, then most of human capital has already been employed in R&D. Hence, job switching at the margin will not raise the growth rate very much because the new inventors are endowed with scanty human capital. Consequently, in the integrated society, a bigger share of human capital is devoted to R&D and a bigger share of labor is devoted to manufacturing, and income is distributed more unequally. This is similar to the case of distribution effects. However, since the perfectly unbalanced integration brings in no human capital, only the most talented laborers of the original society switch job. Hence, although a larger share of population is devoted to manufacturing in the integrated society as a whole, a larger share of population is devoted to R&D in its original part.

Now we are ready to attempt some explanations at real world problems. Jones (1995a) cites a six-fold explosion in the number of scientists and engineers engaged in formal R&D in the United States between 1950 and 1988, from about 160,000 to nearly one million, versus a nearly constant TFP growth as evidence against the "scale effects" prediction of two-sector endogenous growth models. However, this argument suffers from several weaknesses.

First, such a spectacular growth in R&D employment in a *heterogeneous* society naturally leads to the use of less talented scientists and engineers, especially at times when the growth in other types of talent-attracting employment is also spectacular. For example, between 1971 and 1989, the number of Americans offering legal services increased from about 343,000 to just under one million (Reich, 1991, p.192). During the same period, the number of scientists and engineers engaged in formal R&D in the United States rose from 523,500 to 949,300[8] (National Science Board, 1993, Appendix table 3-3).

Fast growth in the legal profession appears to be a response to economic incentives. Between 1987 and 1992, the median annual earnings of American lawyers increased from \$42,328 to \$56,420, an annual growth rate of 5.9%. During the same period, the median annual earnings of American engineers increased from \$37,440 to \$44,824, an annual growth rate of 3.7%, barely keeping pace with inflation (National Science Board, 1993, Appendix table 3-12). A close look may reveal a similar pattern between R&D and other less productive occupations, for example, physicians and financial services.[9] Consequently, the most talented American students choose to go to professional schools such as business, law, and medicine, leaving deficiencies in science and engineering to be made up by the less talented indigene or the talented foreign-born. According to National Science Board (1993, Appendix table 2-28), about half of 1991 Ph.D. recipients of U.S. engineering programs are foreign citizens. Therefore, as a more appropriate proxy for human capital, the quality-adjusted number of scientists and engineers engaged in formal R&D may grow considerably slower than the unadjusted data.

Moreover, like other growth rates related to R&D, this six-fold growth in R&D employment between 1950 and 1988 is subject to the suspicion that part of it "could be spurious, the result of reclassification of informal technological activities into formal R&D under the pressure of tax accountants, public-relations experts, and R&D tax credits" (Griliches, 1994, p.9). The existence of substantial informal R&D activities not only provides the opportunity for "creative accounting" of formal R&D, but also dilutes the growth of total R&D, causing another discrepancy between what we mean to measure and what we actually measure.

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[8] In National Science Board, 1996, Appendix table 3-19, the number of scientists and engineers engaged in R&D in the United States in 1989 is adjusted from 949,300 to 924,200.

[9] Between 1987 and 1992, the median annual earnings of American physicians increased from $36,296 to $52,364, an annual growth rate of 7.6% (National Science Board, 1993, Appendix table 3-3).

Second, unless isolated from the rest of the world, a sovereign nation is not the appropriate unit of observation because technological change has slashed the costs of transportation and communication so drastically that goods and knowledge can flow with unprecedented ease among countries. Coe and Helpman (1995), Lichtenberg and van Pottelsberghe de la Potterie (1996), and chapter 3 of this dissertation have found empirical evidence that a country's total factor productivity depends on not only domestic R&D efforts but foreign R&D efforts as well; and the more open an economy is, the stronger are the beneficial effects of foreign R&D on its growth. In addition, a country may have access to not only a pool of human capital much larger than its own, but also a pool of labor much larger than its own.

The whole world is not the appropriate unit of observation either. This is so not only because different countries are integrated with the rest of the world to different extents, but also because different parts of the same country may be integrated with the rest of the world to different extents. For example, although modern harbors and satellite dishes integrate China's coastal cities well into the world economy, China's inland rural provinces with their more than half billion population are poorly integrated with China's coastal cities and the rest of the world due to out-of-date and insufficient transportation and communication facilities. Therefore, the appropriate unit of observation seems to be *the integrated subworld* that is the weighted aggregation of all countries with weights being appropriate measures of their openness. A first order approximation of the integrated subworld could be the aggregate of all the OECD countries and East Asia newly industrialized economies plus parts of China and India.

If measured properly for the appropriate unit of observation, the relationship between R&D inputs and growth may be well within the explanatory power of unbalanced integration in a heterogeneous world. As waves upon waves of developing countries join the integrated subworld in increasing scales, the demand for human capital and the supply of labor expand rapidly. Rising demand pushes the inventor wage rate up while rising supply drives the laborer wage rate down. Hence, wage inequality between high-skilled workers and low-skilled workers widens substantially in developed countries,[10] motivating the most talented laborers to switch to R&D or its less productive counterparts. Since unbalanced integration is characterized by large increases in L and μ versus a small increase in H, the growth rate of the entire integrated subworld does not rise very much. Furthermore, this modest increase in overall growth rate may manifest itself mainly in the rapid growth of developing countries, leaving developed countries with mediocre growth performance.

Another important implication of our heterogeneous growth model is *convergence*. Although occupations diverge as the integrated subworld becomes more and more heterogeneous, countries may converge. At equilibrium, all countries in this "convergence club" will grow at a common rate but their levels of per capita income will be different if they have different demographic composition. If enough talented inventors are concentrated in some countries, then these countries will have an appreciably higher level of per capita income than the rest of the world. However, since laborers with more or less the same wages are usually an overwhelming majority of the population, countries may converge absolutely.

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[10] At the country and industry levels, more factors have to be taken into account, such as technology (Adams, 1997) and market power (Borjas and Ramey, 1995).

Future Extension of the Model

Although our new heterogeneous vintage of two-sector endogenous growth models, or the heterogeneous growth model in short, has at least qualitatively explained some recent puzzles, it has raised more questions than it has answered. Therefore, all the results of this model should be deemed as tentative and the potential for future extensions is enormous.

Generalized knowledge production function. Jones (1995a, 1995b) argues that two-sector endogenous growth models appear to be inconsistent with time series evidence. Although Jones' empirical evidence may be weak, his theoretical argument is strong. Unfortunately, the model Jones proposes does not include most of the essential features of the real world we mentioned at the beginning of this chapter, and it does not distinguish human capital from labor. As an alternative specification, we plan to modify the knowledge production function as

$$\dot{A} = \delta A^{\phi} H_A^{\lambda}, \tag{26}$$

where ϕ and λ are elasticity parameters. It is straightforward to derive the steady state growth rate

$$g = \frac{\lambda j}{1-\phi}, \tag{27}$$

where j is the growth rate of aggregate human capital. The rest of the derivation should mostly parallel this chapter.

Rent-seeking sector. Although in our model, R&D is the only rewarding activity for human capital and the society treasures knowledge to such an extent that more than 99% of human capital is utilized in its production,[11] the reality is quite different. As noticed by Baumol (1990) and Murphy, Shleifer, and Vishny (1991), and mentioned in the above text, less productive or even unproductive activities of considerable sizes also attract talent with lavish rewards. The ensuing loss of human capital has significant effects on growth, and it is, therefore, almost necessary to extend the current model to include a rent-seeking sector.

Demographic evolution. Under normal circumstances, L increases over time but H and μ can either increase, decrease, or remain constant, depending upon the relative strength of two groups of opposing forces. For example, public education tends to increase H and reduce μ, but the tendency that high-skilled workers have less children and have them at later ages while low-skilled workers (or nonworkers) have more children and have them at earlier ages increase μ and may reduce H.[12] If the former dominates the latter, the demographic evolution is heterogeneity abating. If the latter dominates the former, the demographic evolution (in fact, demographic devolution) is heterogeneity enhancing. If the two balance each other, the demographic evolution is heterogeneity neutral. Demographic evolution is important, especially in long terms, because demographic characteristics determine the relative standard of living.

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[11] See Appendix A, table A-2.

[12] Recent empirical studies show that children of high-skilled workers have higher educational and labor market attainments while children of low-skilled workers (or nonworkers) have lower educational and labor market attainments, implying a weak vertical mobility in American society. See Haveman and Wolfe (1995) for a review.

Demographic evolution is also closely related to government's social policies, especially those about education and welfare.

Political institutions. Once we introduce heterogeneity into our hypothetical society, we introduce politics, too. The bigger μ is, the higher the growth rate, the bigger the income inequality, and the stronger the political demand for redistribution. Given the estimated magnitude of μ, inventors are a political minority. Hence, in a median-voter rule democracy, government policies may be inventor unfriendly and thus growth depressing.[13]

Empirical studies. Our model has already produced several potentially testable hypotheses such as a small trend in the growth rate of the integrated subworld, an increase in the manufacturing share of employment of the integrated subworld, conditional and even absolute convergence of the integrated subworld.

Summary

Existing R&D-based models of economic growth have underscored the fact that the engine of economic growth is technological change, and the fuel of technological change is human capital. However, they have overlooked the fact that human capital is always supplied jointly with but usually demanded separately from labor and the fact that the distribution of human capital is far more skewed than that of labor. This seemingly innocuous neglect has rendered these models not only theoretically flawed but also empirically challenged.

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[13] Bertola (1993) and Alesina and Rodrik (1994) study the relationship between politics and growth in a model of distributive conflict among agents endowed with heterogeneous capital-labor ratio.

This chapter recasts the endogenous technological change model of Romer (1990) in a heterogeneous society where human capital is distributed unequally among the population and is allocated jointly with labor between R&D and manufacturing. Like the real world, this model includes occupational choices based on economic incentives and generates a single-mode, positively skewed wage distribution. Calibration based on observed income differentials and the manufacturing share of employment shows that the inequality in human capital endowment can be of phenomenal magnitudes. This inequality in human capital endowment, in turn, explains inequalities in income, consumption and savings.

Our new heterogeneous vintage of R&D-based models of economic growth is consistent with most of the stylized facts, but the relevant unit of observation is neither any sovereign nation nor the whole world, but rather an integrated subworld. When the integrated subworld expands to incorporate developing economies, it absorbs human capital and labor in proportions more uneven than its own and thus becomes more heterogeneous. As a result, wage differentials increase, workers switch from manufacturing to R&D at the margin, but the growth rate rise only moderately. In addition, since wage rates are the same in the integrated subworld, countries converge, conditional on the human capital endowment of their population.

Our heterogeneous growth model also builds natural bridges connecting the growth theory with some other fields of economics. The bigger the wage differentials, the fiercer the struggle for income redistribution. In addition to politics, heterogeneity also creates information problems. Furthermore, unproductive activities also attract human capital. All these are topics for future research.

CHAPTER 3
INTERNATIONAL R&D SPILLOVERS

Review of Literature

Empirical research on international R&D spillovers has been undergoing rapid development. This research has been stimulated by open-economy, innovation-driven growth models such as those by Grossman and Helpman (1991) and Rivera-Batiz and Romer (1991), and it is also a natural extension of the empirical investigation of intranational R&D spillovers as surveyed by Griliches (1992) and Nadiri (1993).

Researchers in this area have adopted several different approaches. Some treat knowledge spillovers as an externality (Bernstein and Mohnen, 1997; Bernstein and Yan, 1997); others use openness, geographic proximity, or language similarity to gauge the ease with which knowledge flows between nations (Eaton and Kortum, 1996; Park, 1995; Sjöholm, 1996).

One approach pioneered by Coe and Helpman (1995, hereafter CH) is particularly appealing because it incorporates explicitly both the technological component of spillovers and the channel for spillovers in a measure of "foreign R&D capital." In particular, CH measure R&D spillovers received by a country (foreign R&D capital) as a weighted sum of its trade partners' domestic R&D capital stocks, using bilateral import shares as weights. This measure is intended to capture foreign technology embodied in trade flows.

Several recent studies have followed the CH approach. Lichtenberg and van Pottelsberghe de la Potterie (1996, hereafter LP) extend the investigation so as to include not only total imports but also foreign direct investment (FDI) as alternative channels of R&D spillovers in the OECD. Keller (1997) conducts an industry-level study of R&D transmission among OECD countries. Coe, Helpman, and Hoffmaister (1997) extend the investigation to R&D spillovers from the North to the South.

There are several puzzles, however, about the results obtained with the CH approach. First, rates of return to R&D estimated by CH seem "implausibly high" (Barro and Sala-i-Martin, 1995, p.352). Using a sample of 21 OECD countries plus Israel, CH estimate that the own rate of return on R&D investment in a typical Group-Seven (G7) country is about 120 percent (an additional 30 percent accrues to the other countries in the sample). This finding is not consistent, however, with various single-country, firm- and industry-level studies, which indicate that rates of return to R&D in G7 countries typically lie in a range between 20 and 40 percent (Nadiri, 1993, pp.10-12). Second, CH's estimation ranks Japan the second smallest among the 21 countries in the elasticity of TFP with respect to R&D capital of the United States, which contradicts the common belief that Japan is among the top beneficiaries of R&D spillovers from the United States. Third, LP find that inward FDI is not a significant channel of R&D spillovers. This result is at odds with the conventional wisdom that multinational corporations play an important role in the international knowledge diffusion.

We adopt elements of the CH approach, but we differ from them by using new data and modified specifications to reexamine trade and FDI as conduits for R&D spillovers among OECD countries. In contrast to CH and LP who use total imports as knowledge carriers, we focus on capital goods imports. Conceptually, capital goods imports are a better proxy for knowledge carriers than total imports.[1] Formal theories of technological change usually model new technology as embodied in new capital goods. In addition, since capital goods are technologically more sophisticated than noncapital goods, customer training is a more widespread practice among producers of capital goods than among producers of noncapital goods.

The use of capital goods imports helps to resolve several puzzles in the existing literature. Our estimate of the average own rate of return to R&D in G7 countries is about 50 percent, which is close to results from various single-country, firm- and industry-level studies. An additional 30 percent is found to accrue to the other countries in the OECD. Jointly, these two estimates imply very strong international R&D spillovers; more than one third (30/80) of the total benefits of R&D investment in a G7 country accrue to its trade partners within the OECD, as opposed to one fifth (30/150) estimated by CH. Our estimates of spillover elasticities agree with the conventional wisdom. We find that Japan is the second largest (next to Canada) in the elasticity of TFP with respect to R&D stock of the United States. We also find the existence of two "spillover clubs": the Pacific club and the European club, as well as especially high spillover elasticities between Canada and the United States and between Ireland and the United Kingdom.

In our investigation of the role of multinational corporations in international R&D spillovers, we use FDI stocks to proxy multinational corporation activities that transfer technology. Using FDI flow data, LP find that their measure of R&D spillovers embodied in FDI has no effect on host country's TFP, and conclude that inward FDI is not a significant channel of technology diffusion in the OECD. Although we confirm LP's finding that TFP does not depend on a measure of foreign knowledge embodied in FDI, we find a significant correlation between TFP and the intensity of multinational corporation activities in the host country (the ratio of FDI stock to capital stock). We interpret these findings as suggesting that the knowledge transmission mechanisms of FDI are quite different from those of capital goods imports. Thus, further investigation is imperative before any conclusion can be drawn.[2]

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[1] Empirically, Coe, Helpman, and Hoffmaister (1997) also find that capital goods imports data do a better job than total imports data.

We also investigate the role of absorptive capacity in international R&D spillovers. Firm-level studies such as the seminal paper by Cohen and Levinthal (1989) have found that R&D not only generates knowledge but also enhances the ability to absorb knowledge generated elsewhere. This consideration has not been incorporated in either CH or LP. We allow the elasticity of TFP with respect to foreign R&D capital to vary with domestic R&D level, a proxy for absorptive capacity. We find that for relatively large countries (G7 except the United States), domestic R&D activities enhance their ability to absorb foreign knowledge. For small countries (non-G7) and the United States, however, the effect is found to be insignificant.

The rest of this chapter proceeds as follows. First, we discuss the basic regression specification and its extensions. Then, we highlight some main features of the data.

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[2] Kokko (1992) and Blomström and Kokko (1996) provide surveys of studies on international knowledge spillovers through FDI.

Then, we report our empirical findings. And last, we conclude this chapter with a brief summary. Data details are reported in Appendix B.

The Model

Basic Specification

In chapter 2 of this dissertation, the aggregate production function of final goods in a closed economy is formulated as

$$Y = (AL_Y)^{\alpha} K^{1-\alpha} ,$$

where Y is goods output, A is the level of technology characterized by the number of existing designs for intermediate goods, L_Y and K are labor and capital employed in goods production respectively, and α is the labor share of goods output.

Since the R&D sector is competitive and employs only one rivalrous input--human capital, all receipts from the sales of new designs are paid to inventors as wages:

$$P_A \dot{A} = w_H H_A ,$$

where P_A is the price of designs, $\dot{A}$ is the output flow of new designs, w_H is the wage rate of human capital, and H_A is human capital employed in R&D. The above implies that

$$A = \int_{-\infty}^{t} \dot{A} d\tau = \int_{-\infty}^{t} \frac{w_H H_A}{P_A} d\tau .$$

In other words, the level of technology is directly related to the cumulative R&D expenditure, or *R&D capital stock.*

We define total factor productivity (TFP) as $F = Y/L_Y^{\alpha}K^{1-\alpha}$, and there is a simple relationship between total factor productivity and R&D capital stock:

$$\log F = \alpha \log A .$$

In a closed economy, A equals domestic R&D capital stock (A^d). In an open economy, A includes also knowledge diffused from other countries (A^f). Following Coe and Helpman (1995), we assume that

$$A = (A^d)^\delta (A^f)^\phi.$$

This leads, in a panel data setting, to the following relationship between TFP, domestic R&D capital stock, and foreign R&D spillovers:

$$\log F_{it} = c_{it} + \alpha^d_i \log A^d_{it} + \alpha^f_i \log A^f_{it} + \varepsilon_{it}, \tag{1}$$

where i and t are indices of country and time respectively,[3] c is a composite intercept term including both time- and country-specific fixed effects, α^d and α^f are elasticities, and ε is an error term.

First, we postulate that imported capital goods are the major carrier of foreign knowledge spillovers, which is assumed in many theoretical models. Let CGM_{hi} be the amount of capital goods imported by country i from country h, the total amount of knowledge embodied in capital goods imported by country i, A^f_i(CGM), is calculated according to the following equation:

$$A^f_i(\mathrm{CGM}) = \Sigma_h CGM_{hi} A^d_h / CG_h, \tag{2}$$

where CG denotes output of capital goods. In this equation, A^d_h/CG_h gives average knowledge capital contained in each unit of capital goods produced by country h. Therefore, $CGM_{hi}A^d_h/CG_h$ proxies the amount of knowledge embodied in capital goods imported by country i from country h.

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[3] Country and time subscripts will be suppressed in the following text whenever no misunderstanding is caused.

The definition of A^f(CGM) implies that for the same amount of imported capital goods, the importing country obtains more knowledge from a trade partner with high R&D intensity than from a trade partner with low R&D intensity.[4]

Since the data of F, A^d, and A^f have clear trends, we derive our basic specification by taking the first difference of the level specification (1):[5]

$$\Delta \log F_{it} = c_t + \alpha^d{}_i \Delta \log A^d{}_{it} + \alpha^f{}_i \Delta \log A^f{}_{it}(\text{CGM}) + \mu_{it}, \quad (3)$$

where $\Delta x_{it} = x_{it} - x_{it-1}$ for variable x, c is now an intercept term including only the time-specific fixed effects, and μ is an error term.

Second, we adopt a similar specification to examine FDI as an alternative channel of R&D spillovers. Ideally, one would like to calculate R&D spillovers embodied in R&D-related activities of multinational corporations. Due to data availability, the best we can do is to use FDI stock as a proxy for such activities. Let FDI_{hi} be country i's FDI stock from country h, and $A^f{}_i$(FDI) be the total amount of knowledge transmitted by multinational corporations to country i. We calculate $A^f{}_i$(FDI) according to the following equation:

$$A^f{}_i(\text{FDI}) = \Sigma_h FDI_{hi} A^d{}_h / K_h, \quad (4)$$

where K_h is the physical capital stock of FDI-sending country h, and $A^d{}_h/K_h$ gives average knowledge capital per unit of physical capital of country h. By replacing $A^f{}_i$(CGM) with

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[4] CH define A^f as a weighted sum of trade partners' A^d, using bilateral import shares as weights. Their preferred measure of knowledge spillovers is $m\log A^f$, where m denotes the imports-GDP ratio of the importing country. In our empirical implementation, R&D intensity of country h is measured by $A^d{}_h/Y_h$, where Y_h is country h's GDP.

$A^f{}_i$(FDI) in equation (3), we get the basic specification for testing international R&D spillovers through FDI as follows:

$$\Delta\log F_{it} = c_t + \alpha^d{}_i\Delta\log A^d{}_{it} + \alpha^f{}_i\Delta\log A^f{}_{it}(\mathrm{FDI}) + \mu_{it}. \qquad (5)$$

Extensions of the Basic Specification

Equations (3) and (5) are intended to test foreign knowledge embodied in imported capital goods and multinational corporation activities respectively. Trade and FDI are windows to the outside world, but A^f(CGM) and A^f(FDI) may capture only the part of the knowledge spillovers that match the patterns of capital goods trade and FDI respectively. In an attempt to capture the part of knowledge spillovers independent of the pattern of capital goods trade, we use the following extended specification:

$$\Delta\log F_{it} = c_t + \alpha^d{}_i\Delta\log A^d{}_{it} + \alpha^f{}_i\Delta\log A^f{}_{it}(\mathrm{CGM}) + \beta_i\Delta\log(CGM_{it}/Y_{it}) + \mu_{it}, \qquad (6)$$

where CGM_{it}/Y_{it} is the ratio of capital goods imports to GDP in country i. The higher the percentage of capital goods imports in GDP, the wider the window opening to knowledge diffusion from other countries. By replacing $A^f{}_{it}$(CGM) with $A^f{}_{it}$(FDI) and CGM_{it}/Y_{it} with FDI_{it}/K_{it} in equation (6), we have a parallel specification for FDI as follows:

$$\Delta\log F_{it} = c_t + \alpha^d{}_i\Delta\log A^d{}_{it} + \alpha^f{}_i\Delta\log A^f{}_{it}(\mathrm{FDI}) + \beta_i\Delta\log(FDI_{it}/Y_{it}) + \mu_{it}. \qquad (7)$$

Another direction to extend our basic specification is to consider a country's ability to absorb foreign knowledge. We proxy a country's absorptive capacity by its domestic R&D capital stock and assume that

$$\Delta\log F_{it} = c_t + \alpha^d{}_i\Delta\log A^d{}_{it} + \gamma_i\Delta\log A^f{}_{it}(\mathrm{CGM})$$
$$+ \eta_i \log A^d{}_{it}\, \Delta\log A^f{}_{it}\,(\mathrm{CGM}) + \mu_{it}, \qquad (8)$$

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[5] CH uses the level specification in their estimation, presuming that variables are cointegrated. Their cointegration tests yield mixed results, however. The difference

In comparison with specification (3), we are in fact assuming that the elasticity of TFP with respect to the foreign R&D spillovers is directly related to a country's own R&D effort:

$$\alpha^f_{it} = \gamma_i + \eta_i \log A^d_{it}.$$

This implies that a country with more domestic R&D capital is able to benefit more from foreign R&D spillovers.

Data

Our full sample is a panel of 21 OECD countries over the 1983-1990 period.[6] The TFP data are taken from CH and are indexed with 1985 = 1. Following LP, we use values of domestic R&D capital stocks (in 1985 U.S. dollars, based on PPP), which are calculated based on the information provided by CH.[7] We use imports of machinery and transport equipment (SITC 7) as a proxy for imports of capital goods, and FDI stock as a proxy for multinational corporation activities. Details of data construction are reported in Appendix B. Table 3-1 provides summary statistics of key variables.

As shown in table 3-1, TFP increased over the 1983-90 period in all countries except Norway. Japan experienced the largest increase in TFP of 27 percent, while other

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specification is adopted in Coe, Helpman, and Hoffmaister (1997).

[6] The 21 OECD countries are the same as in CH. They are the United States (USA), Japan (JPN), Germany (DEU), France (FRA), Italy (ITA), Great Britain (GBR), Canada (CAN), Australia (AUS), Austria (AUT), Belgium (BEL), Denmark (DNK), Finland (FIN), Greece (GRC), Ireland (IRL), the Netherlands (NLD), Norway (NOR), New Zealand (NZL), Portugal (PRT), Spain (ESP), Sweden (SWE), and Switzerland (CHE). CH's sample also includes Israel.

countries' increase in TFP was between 5 percent (the U.S.) and 18 percent (Finland). Between 1983 and 1990, domestic R&D capital stock increased by a factor between 1.1 (Britain) and 2.5 (Greece). In contrast, foreign R&D capital embodied in capital goods imports increased by a factor between 1.3 (New Zealand) and 3.6 (Spain), and foreign R&D capital embodied in FDI increased by a factor between 1.3 (Sweden) and 2.6 (Japan).

Japan was the least open country in both capital goods imports (0.99 percent of GDP in 1990) and FDI (0.42 percent of domestic physical capital stock in 1990). In contrast, Belgium and Ireland were the most open countries in capital goods imports (about 15 percent of GDP), and Netherlands, Britain and Canada were the most open countries in FDI (more than 10 percent of domestic physical capital stock) among the 13 countries that have FDI data.

G7 countries, the United States in particular, owned most of the R&D stock. The ratio of R&D stock to GDP was very low in Portugal (0.01) and Greece (0.01), but very high in the U.S. (0.23), Germany (0.21), Britain (0.21), and Switzerland (0.21).

The full sample of 21 OECD countries is used in examining international R&D spillovers through capital goods imports. A subsample of 13 countries is used in examining international R&D spillovers through FDI and through simultaneous channels of capital goods imports and FDI.[8]

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[7] CH use indices of R&D capital stocks in their regressions. As LP point out, however, regression results are sensitive to the indexation of R&D capital stocks.

Results

We investigate international R&D spillovers in a standard framework of panel data analysis with both time- and country-specific fixed effects. Since all regressions are estimated in first difference, country-specific fixed effects drop out. In consideration of the great variation in country size, White's heteroscedasticity-consistent covariance estimation method is applied.

Spillovers through CGM: Basic Specification

We first postulate capital goods imports (CGM) as the only channel of international R&D spillovers. Table 3-2 reports estimation results using specification (3). Regressions (2.1) to (2.4) differ in the restrictions on parameters. Notice first that the estimated elasticity of TFP with respect to foreign R&D capital is statistically significant at the 1 percent level, and is remarkably stable, with a value lying in the range between 0.05 and 0.06 in all regressions.

Regression (2.1) shows that the estimated elasticity of TFP with respect to domestic R&D capital is insignificant when restricted to be the same across all countries, an assumption rejected by the F-test. After we divide countries into G7 and non-G7 groups, the estimated elasticity of TFP with respect to domestic R&D capital for G7 countries turns out to be significant, with a value around 0.09, which is similar to 0.08 found by LP (1996, p.20, regression (iv)), but is much smaller than 0.23 obtained by CH (1995, p.869, regression (iii)). It is worth mentioning that studies for industrial countries typically find elasticities of TFP with respect to domestic R&D capital stocks to be in the

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[8] Data availability is the reason that the sample size has to be reduced for the investigation of FDI (see Appendix B).

range of 0.06 to 0.1 (Griliches, 1988, p.15). The estimated elasticity of TFP with respect to domestic R&D capital for non-G7 countries is small and, contrary to CH and LP, insignificant in all regressions. These results highlight the significance of foreign R&D embodied in capital goods imports to the productivity of OECD countries, particularly those small ones.

To see the quantitative significance of spillovers from one country to another, in table 3-3 we calculate the elasticity of TFP with respect to the domestic R&D capital stock of each trade partner based on the estimated coefficients of regression (2.3).[9] Entries in table 3-3 are estimated elasticities of row-country TFP with respect to column-country R&D stock. Table 3-3 shows, for instance, that a one-percent increase in the U.S. R&D capital stock, through capital goods exports to Japan, raises the Japanese TFP by 0.037 percent. On the other hand, a one-percent increase in the Japanese R&D capital stock, through capital goods exports to the U.S., raises the U.S. TFP by 0.025 percent. Table 3-3 also presents the elasticity of domestic TFP and the average elasticity of TFP in all 21 countries.[10]

Table 3-3 reveals several distinctive features of international R&D spillovers. The average elasticity of TFP in all 21 countries gives us a rank of importance of countries as sources of R&D spillovers, descending in the order of the United States,

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[9] The elasticity of country *i*'s TFP with respect to the domestic R&D capital stock of another country *h* is calculated according to the following formula: $\alpha_{hi} = \partial \log F_i / \partial \log A^d_h = \alpha^f_i \partial \log A^f_i / \partial \log A^d_h = \alpha^f_i \, CGM_{hi} A^d_h / (Y_h A^f_i)$.

[10] The average elasticity of TFP in all 21 countries with respect to the domestic R&D capital stock of country h is given by $\alpha_h = \Sigma_i Y_i \alpha_{hi} / Y$, where Y is the sum of GDP over all 21 countries and $\alpha_{ii} = \alpha^d_i$.

Japan, Germany, Britain, France, Canada, and Italy. It shows the average percentage increase in an OECD country's output in response to a one-percent increase in another country's R&D stock. On average, a one-percent increase in the R&D stock of the United States and Japan raises the TFP of an OECD country by 0.054 percent and 0.027 percent respectively.

Table 3-3 also reveals the existence of two "spillover clubs": a Pacific club consisting of the U.S., Japan, Canada, Australia, and New Zealand, and an European club consisting the other 16 countries led by Germany, France, and Britain. Elasticities are significantly higher between members of the same club than between members of different clubs. For example, a one-percent increase in the R&D stock of the United States raises the TFPs of Canada, Japan, Australia, and New Zealand by 0.047, 0.037, 0.028, and 0.024 percent respectively, but it raises none of the TFPs of European countries by more than 0.021 percent. A one-percent increase in the R&D stock of Germany raises the TFP by more than 0.01 percent for every European country (except Ireland), but it raises the TFP by no more than 0.01 percent for every Pacific country.

Especially high elasticities are found between immediate neighbors sharing a common language, for instance, Germany, Austria, and Switzerland. The extreme cases are Canada and Ireland which have very high elasticity with one member of their clubs (the U.S. and the U.K., respectively) but very low elasticities with the others.

Table 3-1. Summary Statistics

Nation	F_{90} / F_{83}	A^d_{90} / A^d_{83}	$A^f_{90}(CGM)$ / $A^f_{83}(CGM)$	$A^f_{90}(FDI)$ / $A^f_{83}(FDI)$	CGM/Y (%)		FDI/K (%)		A^d (billion $)		A^d/Y	
					1983	1990	1983	1990	1983	1990	1983	1990
USA	1.05	1.35	1.52	1.92	2.10	2.90	3.26	6.62	773.1	1041.8	0.21	0.23
JPN	1.27	1.71	2.61	2.60	0.66	0.99	0.34	0.42	152.2	259.6	0.13	0.16
DEU	1.10	1.39	1.89	1.48	4.81	6.77	2.64	2.80	126.3	175.3	0.19	0.21
FRA	1.15	1.27	1.86	1.60	4.59	6.03	3.43	3.80	91.1	115.4	0.15	0.16
ITA	1.12	1.53	2.21	2.11	3.14	4.54	2.63	3.57	30.4	46.4	0.05	0.07
GBR	1.08	1.10	1.56	2.15	6.20	7.18	12.48	17.91	134.3	148.2	0.23	0.21
CAN	1.07	1.58	1.40	1.28	9.27	9.54	14.76	13.71	19.7	31.2	0.06	0.07
AUS	1.06	2.02	1.60	1.85	4.05	5.21	8.56	14.46	4.5	9.1	0.02	0.04
AUT	1.10	1.47	1.94	1.35	8.34	11.26	3.05	2.76	4.5	6.6	0.06	0.07
BEL	1.10	1.37	1.47	NA	14.72	15.48	NA	NA	11.5	15.7	0.12	0.13
DNK	1.06	1.47	1.67	NA	6.32	7.18	NA	NA	3.6	5.3	0.06	0.08
FIN	1.18	1.77	1.76	NA	7.26	7.27	NA	NA	3.1	5.5	0.06	0.09
GRC	1.07	2.50	1.58	NA	6.21	8.53	NA	NA	0.2	0.5	0.00	0.01
IRL	1.17	1.83	1.76	NA	13.22	15.80	NA	NA	0.6	1.1	0.03	0.03
NLD	1.07	1.20	1.73	2.20	9.07	12.18	11.97	21.11	24.2	29.0	0.16	0.15
NOR	0.98	1.43	1.63	1.37	6.89	8.42	4.99	5.48	0.7	1.0	0.02	0.03
NZL	1.13	1.74	1.30	NA	8.47	8.52	NA	NA	3.4	5.9	0.07	0.10
PRT	1.15	1.40	2.19	NA	8.95	13.51	NA	NA	0.5	0.7	0.01	0.01
ESP	1.10	1.89	3.59	NA	3.39	6.46	NA	NA	4.6	8.7	0.02	0.03
SWE	1.06	1.57	1.69	1.32	7.95	8.63	3.11	2.35	13.7	21.5	0.14	0.19
CHE	1.08	1.14	1.73	1.34	7.79	9.59	12.44	10.19	27.3	31.0	0.22	0.21

Notes: F = TFP, A^d = domestic R&D stock, A^f (CGM) = foreign R&D spillovers embodied in capital goods imports, A^f (FDI) = foreign R&D spillovers embodied in FDI, CGM/Y = ratio of capital goods imports to GDP, FDI/K = ratio of FDI stock to domestic capital stock.

Table 3-2. Regression Results: Basic Specification (Pooled Data 1984-1990 for 21 OECD Countries)

Channel	Capital goods imports			
Regression number	2.1	2.2	2.3	2.4
$\Delta\log A^d$	0.005 (0.022)	0.007 (0.022)	0.015 (0.021)	country-specific coefficients
$\Delta G7\log A^d$		0.082 $(0.044)^+$	0.086 (0.041)*	
$\Delta\log A^f$ (CGM)	0.059 (0.013)**	0.058 (0.013)**	0.054 (0.013)**	0.052 (0.012)**
Time effects	No	No	Yes	Yes
R^2	0.147	0.163	0.246	0.417
R^2 adjusted	0.135	0.145	0.196	0.278
Standard error	0.015	0.015	0.015	0.014
Observations	147	147	147	147

Notes: The dependent variable is Δlog (TFP). $\Delta x = x_t - x_{t-1}$ for variable x. A^d = domestic R&D stock, beginning of year; A^f (CGM) = foreign R&D spillovers embodied in capital goods imports, beginning of year; G7 = dummy variable equal to 1 for the seven major countries and equal to 0 for the other countries. Numbers in parentheses are standard errors. "**" indicates significance at the 1% level, "*" indicates significance at the 5% level, and "+" indicates significance at the 10% level.

Table 3-3. Elasticities of TFP with Respect to R&D Capital Stocks in G7 Countries, 1990

Nation	USA	JPN	DEU	FRA	ITA	GBR	CAN
USA		0.0252	0.0081	0.0022	0.0006	0.0053	0.0090
JPN	0.0369		0.0100	0.0012	0.0005	0.0027	0.0002
DEU	0.0122	0.0076		0.0093	0.0022	0.0079	0.0002
FRA	0.0148	0.0044	0.0169		0.0030	0.0071	0.0001
ITA	0.0062	0.0024	0.0213	0.0088		0.0057	0.0001
GBR	0.0144	0.0059	0.0162	0.0056	0.0014		0.0003
CAN	0.0470	0.0034	0.0013	0.0005	0.0001	0.0008	
AUS	0.0276	0.0133	0.0045	0.0009	0.0005	0.0042	0.0004
AUT	0.0054	0.0046	0.0311	0.0024	0.0015	0.0024	0.0001
BEL	0.0060	0.0028	0.0188	0.0086	0.0012	0.0051	0.0001
DNK	0.0111	0.0049	0.0167	0.0028	0.0011	0.0075	0.0001
FIN	0.0111	0.0065	0.0144	0.0027	0.0012	0.0051	0.0003
GRC	0.0042	0.0094	0.0203	0.0048	0.0043	0.0046	0.0001
IRL	0.0202	0.0049	0.0054	0.0020	0.0005	0.0174	0.0002
NLD	0.0100	0.0036	0.0179	0.0038	0.0009	0.0083	0.0003
NZL	0.0240	0.0127	0.0035	0.0009	0.0006	0.0057	0.0003
NOR	0.0164	0.0042	0.0119	0.0021	0.0007	0.0072	0.0002
PRT	0.0029	0.0036	0.0137	0.0086	0.0039	0.0092	0.0000
ESP	0.0109	0.0041	0.0157	0.0086	0.0031	0.0057	0.0001
SWE	0.0146	0.0049	0.0164	0.0030	0.0011	0.0059	0.0002
CHE	0.0075	0.0049	0.0255	0.0044	0.0020	0.0039	0.0001
Average elasticity of TFP in all 21 countries	0.0537	0.0270	0.0184	0.0099	0.0073	0.0113	0.0078
Elasticity of domestic TFP	0.1010	0.1010	0.1010	0.1010	0.1010	0.1010	0.1010

Notes: Entries are estimated elasticities of TFP in the row country with respect to the R&D capital stock in the column country. Based on regression (2.3) in table 3-2. Averages are calculated using PPP-based GDP weights.

Table 3-4. Regression Results: Extended Specification (Pooled Data 1984-1990 for 21 OECD Countries)

Channel	Capital goods imports			
Regression number	4.1	4.2	4.3	4.4
$\Delta\log A^d$	0.007 (0.022)	0.010 (0.022)	0.008 (0.022)	0.016 (0.021)
$\Delta G7\log A^d$	0.082 $(0.044)^+$	0.086 (0.043)*	0.083 $(0.043)^+$	0.087 (0.041)*
$\Delta\log A^f$(CGM)	0.058 (0.013)**		0.036 $(0.020)^+$	0.043 (0.020)*
Δlog (CGM/Y)		0.058 (0.014)**	0.026 (0.022)	0.014 (0.022)
Time effects	No	No	No	Yes
R^2	0.163	0.154	0.171	0.248
R^2 adjusted	0.145	0.137	0.148	0.192
Standard error	0.015	0.015	0.015	0.015
Observations	147	147	147	147

Notes: The dependent variable is Δlog (TFP). CGM/Y = ratio of capital goods imports to GDP. See the notes below table 3-2 for definitions of other variables.

Table 3-5. Regression Results: Extended Specification (Pooled Data 1984-1990 for 21 OECD Countries)

Channel	Capital goods imports			
Regression number	5.1	5.2	5.3	5.4
$\Delta \log A^d$	0.007 (0.022)	0.005 (0.022)	0.007 (0.022)	0.014 (0.021)
$\Delta G7 \log A^d$	0.082 $(0.044)^+$	0.071 (0.054)	0.010 (0.059)	0.028 (0.053)
$\Delta \log A^f$(CGM)	0.058 (0.013)**	0.063 (0.015)**	0.060 (0.015)**	0.059 (0.016)**
$\log A^d \Delta \log A^f$ (CGM)		-0.007 (0.008)	-0.006 (0.008)	-0.006 (0.008)
$G7^*\log A^d \Delta \log A^f$ (CGM)		0.006 (0.008)	0.016 $(0.009)^+$	0.014 (0.009)
$US^*\log A^d \Delta \log A^f$ (CGM)			-0.015 (0.005)**	-0.017 (0.006)**
Time effects	No	No	No	Yes
R^2	0.163	0.167	0.189	0.275
R^2 adjusted	0.145	0.137	0.154	0.210
Standard error	0.015	0.015	0.015	0.015
Observations	147	147	147	147

Notes: The dependent variable is Δlog (TFP). US = dummy variable equal to 1 for the United States and 0 for the other countries. See the notes below table 3-2 for definitions of other variables.

Table 3-6. Regression Results: Extended Specification (Pooled Data 1984-1990 for 13 OECD Countries)

Channel	Foreign direct investment			
Regression number	6.1	6.2	6.3	6.4
$\Delta \log A^d$	-0.014 (0.061)	-0.010 (0.062)	-0.011 (0.063)	0.005 (0.061)
$\Delta G7 \log A^d$	0.120 $(0.058)^+$	0.120 (0.057)*	0.127 (0.056)*	0.126 (0.053)*
$\Delta \log A^f$ (FDI)	0.007 (0.014)		-0.023 (0.021)	
$\Delta \log$ (FDI/K)		0.021 $(0.011)^+$	0.035 (0.016)*	-0.001 (0.015)
Time effects	No	No	No	Yes
R^2	0.054	0.079	0.091	0.208
R^2 adjusted	0.022	0.048	0.049	0.120
Standard error	0.015	0.015	0.015	0.014
Observations	91	91	91	91

Notes: The dependent variable is $\Delta \log$ (TFP). A^f (FDI) = foreign R&D spillovers embodied in foreign direct investment, beginning of year; FDI/K = ratio of FDI stock to domestic capital stock. See the notes below table 3-2 for definitions of other variables.

Table 3-7. Regression Results: Extended Specification (Pooled Data 1984-1990 for 13 OECD Countries)

Channel	Capital goods imports vs. foreign direct investment				
Regression number	7.1	7.2	7.3	7.4	7.5
$\Delta \log A^d$	-0.007 (0.063)	0.000 (0.064)	-0.010 (0.062)	-0.004 (0.065)	0.000 (0.064)
$\Delta G7 \log A^d$	0.096 (0.052)$^{+}$	0.105 (0.052)*	0.120 (0.057)*	0.094 (0.052)$^{+}$	0.105 (0.052)*
$\Delta \log A^f$ (CGM)	0.068 (0.016)**			0.065 (0.016)**	
$\Delta \log$ (CGM/Y)		0.075 (0.015)**			0.074 (0.017)**
$\Delta \log$ (FDI/K)			0.021 (0.011)$^{+}$	0.015 (0.010)	0.001 (0.012)
Time effects	No	No	No	No	No
R^2	0.213	0.237	0.079	0.227	0.238
R^2 adjusted	0.186	0.211	0.048	0.192	0.202
Standard error	0.014	0.014	0.015	0.014	0.014
Observations	91	91	91	91	91

Notes: The dependent variable is $\Delta \log$ (TFP). See the notes below tables 3-2, 3-4, and 3-6 for definitions of other variables.

Table 3-3 also confirms a common belief that Japan is one of the largest beneficiaries of the U.S. technology. In table 3-3, Japan is the second largest (next to Canada) in the elasticity of TFP with respect to the U.S. R&D stock. In contrast, CH's table 5 ranks Japan the second smallest among 20 OECD countries plus Israel.

We also calculate the social rates of return to R&D investment based on regression (2.3). The own rate of return is defined as $r_{ii} = \partial Y_i/\partial A^d_i = \alpha^d_i Y_i/A^d_i$ For G7 countries in 1990, the average own rate of return is 53 percent, which is less than one half of what is found by CH (123 percent, p.876), but is consistent with a vast literature of firm- and industry-level studies.[11] For non-G7 countries, the average own rate of return is 16 percent, much lower than 85 percent found by CH and 63 percent obtained by LP.

The cross rate of return from R&D investment is defined as $r_{hi} = \partial Y_i/\partial A^d_h = \alpha_{hi} Y_i/A^d_h$. The OECD-wide rate of return from R&D investment is defined as $r_h = \Sigma_i r_{hi} = \partial Y/\partial A^d_h = \alpha_h Y/A^d_h = \Sigma_i \alpha_{hi} Y_i/A^d_h$, where Y is the sum of GDP over all 21 countries, $\alpha_h = \Sigma_i \alpha_{hi} Y_i/Y$ is the average elasticity of TFP in all 21 countries, and $\alpha_{ii} = \alpha^d_i$. We find that for G7 countries in 1990, the OECD-wide rate of return from investment in R&D is 83 percent, which is lower than the 155 percent found by CH. For G7 countries, therefore, the difference between the OECD-wide and the own rates of return is about 30 percent, which implies that more than one third (30/83) of the total benefits of R&D investment in a G7 country accrue to its trade partners within the OECD, an estimate significantly higher than that of CH (32/155).

Spillovers through CGM: Extended Specifications

In specification (6), we include CGM-GDP ratio to see if it can account for general knowledge spillover effects related to capital goods imports. Regression (4.2) in table 3-4 shows that, when entering the regression alone, *CGM/Y* acts as a measure of openness and is statistically significant at the 1 percent level. Regressions (4.3) and (4.4) show that when both A^f(CGM) and *CGM/Y* are included in the same regression, *CGM/Y* is no longer significant. These results indicate that the knowledge contents of imports matter.

In specification (8), we assume that the elasticity of TFP with respect to A^f(CGM) depends on a country's absorptive capacity proxied by its domestic R&D capital. In our empirical implementation, we use a G7 dummy and a US dummy. The United States is considered to be different from other G7 countries because it is clearly the leader of world R&D activity and its level of domestic R&D is likely to be a poor measure of absorptive capacity. Regression (5.3) in table 3-5 shows that for relative large OECD countries (G7 except the U.S.), domestic R&D is important for absorbing foreign knowledge embodied in capital goods imports. For relatively small OECD countries (non-G7) as well as the United States, domestic R&D stock may not be a good measure of absorptive capacity.

Spillovers through FDI

Next we investigate foreign direct investment (FDI) as a channel of international R&D spillovers. Conceptually, it is much more difficult to measure foreign R&D

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[11] Nadiri (1993, pp.10-12) summarizes that rates of return reported in dozens of studies using industry data from the U.S., Japan, Canada, Britain, Germany, or France typically lie in a range between 20 and 40 percent.

embodied in FDI, because there is no good measure of R&D-related activities by multinational corporations. In our investigation, we use FDI stock as a proxy for the size of R&D-related activities by multinational corporations. Although this is a poor proxy, there is no better alternative. All FDI-related regressions are based on a sample of 13 OECD countries over the period 1983-1990.

Table 3-6 reports estimation results using specifications (5) and (7). The variable A^f(FDI) is intended to measure foreign knowledge embodied in FDI, but it turns out to be insignificant (regression (6.1)). This may result from A^f(FDI) not being a good measure of foreign knowledge embodied in FDI. In regressions (6.2), (6.3), and (6.4), we use the FDI intensity, *FDI/K*, to account for general knowledge spillovers through FDI. The higher *FDI/K* is, the more foreign knowledge multinational corporations transmit to the host country. This ratio turns out to be statistically significant in regressions (6.2) and (6.3). It becomes insignificant when we include time-specific fixed effects (regression (6.4)). Our results suggest that FDI may be another channel of international knowledge spillovers, but its transmission mechanisms may be quite different from those of capital goods imports. Thus, further investigation is imperative before any conclusion can be drawn.

Simultaneous Channels of Spillovers

Finally we investigate CGM and FDI in the same regression. For comparison, we replicate regressions (2.2) and (4.2) as regressions (7.1) and (7.2) in table 3-7 for the 13-country sample. The results from the 13-country sample are very similar to those from the 21-country sample. This again shows the robustness of our findings about spillovers through capital goods imports.

Regression (7.3) shows that, when entering the regression alone, *FDI/K* is significant. Regression (7.4) shows that when both A^f(CGM) and *FDI/K* are included in the same regression, *FDI/K* is still marginally significant. However, regression (7.5) shows that when both *CGM/Y* and *FDI/K* are included in the same regression, *FDI/K* becomes insignificant. Since the correlation between *CGM/Y* and *FDI/K* is 0.78, these results suggest that the effects of FDI on knowledge spillovers may be overlapped to some extent with the effects of CGM on knowledge spillovers, especially the part of effects captured by *CGM/Y*.

Summary

This chapter investigates international R&D spillovers through trade and FDI among industrialized countries. Our results show that capital goods trade is a significant spillover channel; more than one third of the total benefits of R&D investment in a G7 country accrue to its trade partners. Although no correlation is found between TFP and a measure of foreign R&D embodied in FDI, a significant correlation is found between TFP and the intensity of FDI. In addition, we find that domestic R&D activities enhance the ability of relatively large countries (G7 except the United States) to absorb foreign technology transmitted through trade.

Our estimates of the effects of R&D spillovers through capital goods trade are robust and are consistent with results from single-country, firm- and industry-level studies. Our estimates of the effects of R&D spillovers through FDI should be interpreted with caution, however, because of the poor quality of FDI data. Further research explorations with better measure of R&D activities of multinational corporations will be useful. The importance of absorptive capacity in international R&D transmission also deserves more attention.

CHAPTER 4
INTERNATIONAL AND INTERSECTORAL R&D SPILLOVERS

Review of Literature

The evolution of empirical studies of R&D spillovers is governed by the availability of data and by our theoretical grasp of the limits to technology transfer. Within a country, data at the firm, regional, and industry levels are usually gathered by the same statistical agency according to a consistent system of definitions about the units of observation and variables. Therefore, it was natural that the first successes were achieved in the identification of interfirm, interregional, and interindustry spillovers within a particular country (Bernstein and Nadiri, 1988; Jaffe, 1986; Terleckyj, 1974).

At the aggregate level, where units of observation are well defined, the harmonization efforts of the OECD and other international organizations have produced internationally comparable data of adequate quality. Hence, empirical studies of international R&D spillovers flourished at the country level in the early stage (Coe and Helpman, 1995; Park, 1995).

However, definitions of industries vary across countries. As a result, the harmonization efforts of the OECD and other international organizations have been far less successful at the sectoral level than at the national level. Consequently, exploration of simultaneous international and intersectoral spillovers is still in its infancy (Keller, 1997).

Like the empirical studies of international R&D spillovers at the aggregate level, empirical investigation of simultaneous international and intersectoral R&D spillovers draws heavily on the literature of domestic R&D spillovers, especially in identifying interindustry spillovers. According to the way in which interindustry spillovers are modeled, the literature of domestic R&D spillovers can be divided into three categories: the externality approach, the distance approach, and the flow approach.

The externality approach incorporates into one industry's production function or cost function the R&D pools of other industries directly (Bernstein and Nadiri, 1988). The main difficulty in extending this approach to simultaneous international and intersectoral spillovers is that because of the problem of identification, the number of R&D pools included is limited.

The distance approach assumes that knowledge does not flow frictionlessly between sectors. It uses the patent or R&D profiles of industries to calculate a correlation coefficient between the patent or R&D of any two industries. It then uses the correlation measures as weights to construct the weighted sum of other industries' R&D as the measure of spillovers into any industry (Jaffe, 1986; Adams, 1990; Adams and Jaffe, 1996). The main difficulty in extending this approach to simultaneous international and intersectoral spillovers is the sheer quantity of data required about the patent or R&D profiles of industries.

The flow approach assumes that technology is embodied in cross-industry input-output flows of patents, intermediate goods, or capital goods and is consequently restricted by those flows. It uses normalized flows as weights to construct the weighted sum of other industries' R&D as the measure of spillovers into any industry. The main difficulty in extending this approach to simultaneous international and intersectoral spillovers is the sheer quantity of data required about the patent or trade flows between industries.

The first input-output table used for this purpose that I am aware of was that used by Terleckyj (1974) in his study of the domestic intersectoral transmission of technology. Scherer (1982, 1984) also constructed domestic cross-industry patent flows by reclassifying a large sample of patents by both industry of origin and industry of use, and used the count percentage to redistribute the R&D of industries of origin to industries of use. Evenson, Putnam, and Kortum (1991) construct a patent input-output table based on Canadian patent data (the only national patent data in the world classified by both industry of origin and industry of use).

Keller (1997) studies simultaneous international and intersectoral R&D spillovers using the flow approach based on a sample of thirteen manufacturing industries in eight OECD countries over the period 1970-1991. To model the cross-sector R&D flows, he uses country- and time-invariant input-output tables of domestic and imported intermediate goods. As an alternative, he also uses the patent input-output table constructed by Evenson, Putnam, and Kortum (1991) based on Canadian patent data. His results not only confirm the earlier findings at the aggregate level that there are significant international R&D spillovers but also indicate the existence of intersectoral R&D spillovers.

In this chapter, we extend our empirical investigation of international R&D spillovers to simultaneous international and intersectoral R&D spillovers. We depart from the existing literature in several important respects. First, we use country- and time-specific input-output tables of capital formation while the existing literature uses country- and time-invariant input-output tables of intermediate goods. Second, since TFP measures tend to be error-ridden at the sectoral level, we also investigate the impact of R&D spillovers on the average real wage, which is closely linked to productivity. Third, our sample includes total services.

The rest of the chapter proceeds as follows. First, we derive the empirical specification based on the theoretical model of chapter 2. Next, we highlight some main features of the data. Then, we report our empirical findings. And last, we conclude this chapter with a brief summary. Details of data construction are described in Appendix C.

The Model

TFP and Spillovers

In chapter 3 of this dissertation, we formulate the international R&D spillovers at the country level as follows:

$$\log F_i = c_i + \alpha_i^d \log A_i^d + \alpha_i^f \log A_i^f + \varepsilon_i,$$

where F_i is the total factor productivity of country i, c_i is a composite intercept term, α^d_i and α^f_i are elasticities, A^d_i is the R&D stock of country i, A^f_i is the R&D spillovers to country i, and ε_i is an error term.

The R&D spillovers to country i is constructed as a weighted sum of R&D stocks of countries other than i, with *normalized* bilateral flows of goods or patents used as weights:

$$A_i^f = \sum_{h \neq i} W_{hi} A_h^d .$$

One purpose of normalization is to cancel the currency units out of bilateral flows so that the weights are pure numbers. The result is that R&D spillovers are in the same units as R&D stocks. Another purpose of normalization is to scale down bilateral flows so that the weights are less than one. The result is that only part of an origin country's R&D stock is included in a destination country's R&D spillovers.[1]

The above formulation implies that R&D spillovers from all foreign countries are *substitutes* for each other from the standpoint of the receiving country. This assumption may be a reasonable one, especially if international technology market is relatively competitive.

At the sectoral level, we adopt a five-dimension "*hijkt*" subscript system to classify spillovers. Here *h* denotes the spillover-emitting country, *i* denotes the spillover-receiving country, *j* denotes the spillover-emitting industry, *k* denotes the spillover-receiving industry, and *t* denotes the year. I will suppress the year subscript in the following text whenever no confusion is caused by doing so.

A simple extension of the above formulation of international R&D spillovers leads to the following econometric model of international and intersectoral R&D spillovers:

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[1] Coe and Helpman (1995) construct their weights by dividing the trade flow from country *h* to country *i* (M_{hi}) by country *i*'s total imports ($M_i = \Sigma_{h\neq i}M_{hi}$). The term "normalization" follows from the fact that their weights ($W_{hi} = M_{hi}/M_i$) sum to one across all origin countries. Coe and Helpman's normalization scheme is not only *ad hoc* but also empirically dominated by that of Lichtenberg and van Pottelsberghe de la Potterie (1996). Lichtenberg and van Pottelsberghe de la Potterie construct their weights by dividing the trade flow from country *h* to country *i* (M_{hi}) by country *h*'s GDP (Y_h). Hence, the standard assumption that country *i*'s spillovers pool equals the weighted sum of origin countries' R&D stocks ($A_i^f = \Sigma_{h\neq i}W_{hi}A_h^d = \Sigma_{h\neq i}M_{hi}A_h^d/Y_h$) is equivalent to assuming that a country's R&D stock is evenly embodied in its output, and thus when it exports goods, its R&D stock is proportionately "exported". This may be a reasonable assumption from the viewpoint of "embodied" spillovers.

$$\log F_{ik} = c_{ik} + \alpha_{ik}^{do} \log A_{ik}^{do} + \alpha_{ik}^{dc} \log A_{ik}^{dc} + \alpha_{ik}^{f} \log A_{ik}^{f} + \varepsilon_{ik}, \tag{1}$$

where F_{ik} is the total factor productivity of sector k in country i, c_{ik} is an intercept term, $\alpha^{do}{}_{ik}$, $\alpha^{dc}{}_{ik}$, and $\alpha^{f}{}_{ik}$ are elasticities, $A^{do}{}_{ik}$ is the domestic own-sector R&D stock of sector k in country i, $A^{dc}{}_{ik}$ is the domestic cross-sector R&D spillovers to sector k in country i, $A^{f}{}_{ik}$ is the foreign R&D spillovers to sector k in country i, and ε_{ik} is an error term.

Under the assumption that R&D spillovers are embodied in capital goods flows, the domestic cross-sector R&D spillovers is constructed as

$$A_{ik}^{dc} = \sum_{j \neq k} \frac{CGM_{iijk}}{Y_{ij}} A_{ij}^{do}, \tag{2}$$

where CGM_{iijk} is the domestic capital goods flow, Y_{ij} is the GDP of a domestic spillover-sending sector and is used here as the normalization factor.

Under the same assumption, the foreign R&D spillovers is constructed as

$$A_{ik}^{f} = \sum_{j} \sum_{h \neq i} \frac{CGM_{hijk}}{Y_{hj}} A_{hj}^{do}, \tag{3}$$ [2]

where CGM_{hijk} is the imported capital goods flow, Y_{hj} is the GDP of a foreign spillover-sending sector and is used here as the normalization factor.

A merit of this formulation is that it may tell us explicitly whether the prevalent mode of spillovers is cross-country or cross-sector. One potential problem with this formulation is that it assumes that all spillovers are mediated by capital goods. Thus, if there is no capital goods flow between two sectors, then the spillovers between these two sectors are assumed to be zero. This may not be true, especially in the case of international within-sector spillovers. Another disadvantage of this formulation is the use of TFP as the dependent variable. At the sectoral level, TFP is difficult to measure with adequate accuracy.

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[2] Foreign R&D spillovers can be further divided into foreign own-sector and foreign cross-sector spillovers as in Keller (1997). However, we have two practical difficulties here. First, a lot of zeros along the diagonal of table 4-2 imply that foreign own-sector

Wages and Spillovers

Since wages are easier to measure accurately than productivity and a relationship between wages and spillovers can be derived from our theoretical model in chapter 1 of this dissertation, we use wages as the dependent variable in an alternative formulation of international and intersectoral R&D spillovers.

According to equation (A38) of Appendix A, the average wage along the balanced growth path is

$$G = \frac{W}{L} = \frac{\alpha\left[r + (1-\alpha)g\right]Y}{rL}, \tag{4}$$

where W is aggregate wage income, L is total employment, α is the labor share of goods output, g is growth rate, r is rate of return, and Y is goods output.

According to equation (A39) of Appendix A,

$$Y = \mu^{\frac{\alpha-1}{\alpha}}(1-\alpha)^{\frac{1-\alpha}{\alpha}}(\delta H)^{\frac{\alpha-1}{\alpha}}\left[\frac{\sigma + \frac{\rho}{\delta H}}{\mu(1-\alpha)+\sigma}\right]^{\frac{\alpha-1}{\alpha}+\frac{1}{\mu}} LA, \tag{5}$$

where μ is the distribution parameter of human capital endowment, σ is the inverse of the elasticity of intertemporal substitution, ρ is the subjective discount rate, δ is the productivity

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spillovers captured by capital goods imports are also zeros. Second, more explanatory variables of similar nature mean a larger chance of having the multicollinearity problem.

parameter of knowledge production, H is the aggregate human capital endowment, A is the level of technology.

Combining (4) and (5), we can express the relationship between G and A as

$$G = \Pi(\mathrm{g}, \mathrm{r})A, \tag{6}$$

where Π is also a function of all the above-mentioned parameters and thus is constant along the balanced growth path.

In an open, multi-sector economy *i*, the technology level of sector *k* (A_{ik}) depends on not only the domestic own-sector R&D capital (A^{do}_{ik}) but also the domestic cross-sector R&D spillovers (A^{dc}_{ik}) and the foreign R&D spillovers (A^{f}_{ik}). Assuming A_{ik} is a Cobb-Douglas function of A^{do}_{ik}, A^{dc}_{ik}, and A^{f}_{ik}, the effects of R&D spillovers on wages can be formulated as

$$\log G_{ik} = c_{ik} + \alpha^{do}_{ik} \log A^{do}_{ik} + \alpha^{dc}_{ik} \log A^{dc}_{ik} + \alpha^{f}_{ik} \log A^{f}_{ik} + \varepsilon_{ik}, \tag{7}$$

where c_{ik} is an intercept term and ε_{ik} is an error term.

Data

Our sample is a panel of fourteen sectors in five major OECD countries over the 1978-1990 period. The five countries are Germany (DEU), France (FRA), Great Britain (GBR), Japan (JPN), and the United States (USA).

The fourteen industries are Food, Beverages & Tobacco (ISIC 31), Textiles, Apparel & Leather (ISIC 32), Wood Products & Furniture (ISIC 33), Paper, Paper Products & Printing (ISIC 34), Chemical Products (ISIC 35), Non-Metallic Mineral Products (ISIC 36), Basic Metal Industries (ISIC 37), Metal Products (ISIC 381), Non-

Electrical Machinery (ISIC 382), Electrical Machinery (ISIC 383), Transport Equipment (ISIC 384), Professional Goods (ISIC 385), Other Manufacturing (ISIC 39), Total Services (ISIC 4+5+6+7+8+9).

Note that data are missing for Wood Products & Furniture (ISIC 33) in Japan, Chemical Products (ISIC 35) in Great Britain, and Other Manufacturing (ISIC 39) in France. Therefore, we actually have data for 67 cross-sectional units over 13 time periods, or a total of 871 observations.

Seven variables are used in our regressions, and they are constructed based on data from five OECD databases. The seven variables are physical capital stock per worker (K), average real wage (G), total factor productivity constructed with fixed shares of labor (F^{fs}), total factor productivity constructed with revenue shares of labor (F^{rs}), domestic own-sector R&D stock (A^{do}), domestic cross-sector R&D spillovers (A^{dc}), and foreign R&D spillovers (A^{f}).

The five databases are the International Sectoral Database (ISDB), the Structural Analysis Database (STAN), the OECD Input-Output Database (I/O), the Bilateral Trade Database (BTD), the Analytical Business Enterprise Research and Development Database (ANBERD) (supplemented by unpublished 1963-1972 data from OECD archives).

Physical capital stock per worker, average real wage and TFPs are constructed based on raw data from ISDB and, as a supplement to ISDB, STAN. Domestic own-sector R&D stocks are constructed based on R&D flow data from ANBERD supplemented by unpublished 1963-1972 data. R&D spillovers are constructed by combining domestic own-sector R&D stocks with the normalized cross-country, cross-sector bilateral trade flows of capital goods. The cross-country, cross-sector bilateral trade flows of capital goods, in turn, are obtained by combining the domestic and imported capital formation tables of I/O with the within-sector import shares calculated based on data from BTD. Details of the data construction are reported in Appendix C.

Table 4-1 gives an example of the domestic capital formation tables (France, 1990) in the OECD Input-Output Database. Table 4-2 gives an example of the imported capital formation tables (France, 1990). These two tables demonstrate two important features of capital goods flows. First, there are a lot of zero entries in both capital formation tables because some industries do not produce capital goods. Since we formulate spillovers as embodied in capital goods, zero capital flows imply zero spillovers. This may be true for cross-sector spillovers but may not for within-sector spillovers.

Second, the domestic capital formation table and the imported capital formation table are highly correlated, especially when Total Services (ISIC 4+5+6+7+8+9) is excluded.[3] Since domestic cross-sector spillovers are constructed based on domestic capital formation tables and foreign spillovers are constructed based on imported capital formation tables, the high correlation between domestic and foreign capital formation tables may result in high correlation between domestic cross-sector spillovers and foreign spillovers, causing the multicollinearity problem.

Table 4-3 reports the revenue share of labor used in the construction of TFP. There are wild variations in the labor revenue share across countries and across sectors. In most sectors, Japan has the lowest labor revenue share while Great Britain has the highest. In most countries, the labor revenue share is low in Food, Beverages & Tobacco (ISIC 31), Chemical Products (ISIC 35), and Total Services (ISIC 4+5+6+7+8+9) while it is high in Textiles, Apparel & Leather (ISIC 32), Metal Products (ISIC 381), Non-Electrical Machinery (ISIC 382), Electrical Machinery (ISIC 383), and Transport Equipment (ISIC 384).

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[3] According to the documentation of the OECD Input-Output Database, imported flows of capital goods are usually estimated in proportion to domestic flows of capital goods.

Some of these variations are normal, the manifestation of differences in technological conditions. However, some of these variations are abnormal, the aftermath of the industrial policies of national governments and measurement errors. For example, the labor revenue shares of Transport Equipment (ISIC 384) and Basic Metal Industries (ISIC 37) in Great Britain are exceedingly high, showing how far away the British Government carried them from competition during this period.

The break-down of the competitive condition implies that to use labor revenue shares to calculate TFP will cause excessive variations in the calculated TFP measures. Table 4-4 and table 4-5 report the summary statistics. In table 4-4 the column for TFP constructed with the labor revenue share (F^{rs}) shows wild cross-sector and within-sector variations. Excessive variations in TFP constructed with the labor revenue share (F^{rs}) are also evident in table 4-6 which reports simple statistics for the log of variables.

Hence, this "proportionality hypothesis" is the source of the high correlation between domestic and imported capital formation tables.

Table 4-1. Domestic Capital Formation Table of France, 1990

Sector	31	32	33	34	35	36	37	381	382	383	384	385	39	4+5+6+ 7+8+9
31	0	0	0	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	0	0
33	326	123	53	260	493	43	185	95	244	132	261	27	22	3616
34	0	0	0	0	0	0	0	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0	0	0	0	0	0	0	0
36	0	0	0	0	0	0	0	0	0	0	0	0	0	0
37	0	0	0	0	0	0	0	0	0	0	0	0	0	0
381	890	943	437	1462	4590	259	1072	3778	3448	1902	5741	433	188	14223
382	9330	3151	1630	7122	12565	990	4350	5707	5812	2808	7380	844	699	37163
383	1226	377	206	1681	4299	338	2239	1118	1986	1408	1986	270	88	40559
384	1889	357	553	464	64	122	45	639	554	430	256	69	237	42962
385	87	12	145	169	602	27	63	26	97	82	183	11	62	6716
39	0	0	0	0	0	0	0	0	0	0	0	0	0	1704
4+5+6+ 7+8+9	9320	1855	1635	3265	12404	696	2569	3758	4052	2490	8813	531	699	570706

Note: Entries are flows of capital goods from row sectors to column sectors in millions of national currency units at current prices.

Table 4-2. Imported Capital Formation Table of France, 1990

Sector	31	32	33	34	35	36	37	381	382	383	384	385	39	4+5+6+ 7+8+9
31	0	0	0	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	0	0
33	125	47	20	99	189	16	71	36	94	50	100	11	9	1379
34	0	0	0	0	0	0	0	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0	0	0	0	0	0	0	0
36	0	0	0	0	0	0	0	0	0	0	0	0	0	0
37	0	0	0	0	0	0	0	0	0	0	0	0	0	0
381	59	62	29	97	303	17	71	249	227	126	379	29	12	938
382	5985	2224	1046	4917	8498	653	2867	3646	4753	2822	5007	561	449	54575
383	306	95	52	421	1080	85	553	278	497	356	498	68	22	10295
384	1740	328	509	427	580	113	73	589	509	396	235	64	218	38587
385	48	7	80	94	333	15	35	14	53	44	103	6	34	3710
39	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4+5+6+ 7+8+9	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Note: Entries are flows of capital goods from row sectors to column sectors in millions of national currency units at current prices.

Table 4-3. Labor Revenue Shares: 1978-1990 Averages

Sector	Nation				
	DEU	FRA	GBR	JPN	USA
31	0.432	0.527	0.588	0.368	0.525
32	0.725	0.725	0.849	0.701	0.779
33	0.748	0.643	0.847	N/A	0.669
34	0.690	0.688	0.775	0.475	0.672
35	0.539	0.457	N/A	0.281	0.532
36	0.640	0.607	0.672	0.551	0.753
37	0.756	0.666	0.889	0.363	0.752
381	0.743	0.704	0.806	0.771	0.743
382	0.851	0.758	0.848	0.614	0.779
383	0.776	0.708	0.821	0.543	0.747
384	0.755	0.785	0.929	0.511	0.796
385	0.756	0.625	0.639	0.579	0.786
39	0.541	N/A	0.784	0.628	0.613
4+5+6+7+8+9	0.432	0.450	0.521	0.485	0.512

Table 4-4. Summary Statistics: 1990 Levels

Sector	Nation	F^{fs}_{90}	F^{rs}_{90}	G_{90} ($)	K_{90} ($)	A^{do}_{90} (mill. $)	A^{dc}_{90} (mill. $)	A^{f}_{90} (mill. $)
31	DEU	1227	63	14078	67271	901	1028	158
	FRA	1238	169	20110	101235	936	708	362
	GBR	1131	314	20296	95655	1481	451	243
	JPN	1289	35	13815	54009	4755	1935	128
	USA	1652	219	24960	102125	6784	4571	364
32	DEU	850	1115	14732	45007	443	314	52
	FRA	947	1241	16909	53736	349	204	111
	GBR	682	3289	13134	38454	352	105	96
	JPN	368	374	6916	38862	1882	909	66
	USA	1146	2607	19569	32853	1364	1772	137
33	DEU	867	1430	14683	36360	398	253	41
	FRA	999	536	15607	52686	50	155	80
	GBR	822	3852	16291	36415	47	243	151
	JPN	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	USA	1282	923	20827	38693	1094	1646	118
34	DEU	1076	960	20016	64830	300	722	114
	FRA	1161	1014	21633	75502	195	515	240
	GBR	1313	2985	25746	57983	329	278	299
	JPN	1010	63	18996	223843	1587	1989	135
	USA	1386	1005	27258	82644	4520	8822	669
35	DEU	1522	243	26128	86851	24764	2089	333
	FRA	1719	94	26785	160328	13417	987	431
	GBR	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	JPN	2487	13	29942	292781	35601	3628	268
	USA	1852	240	34850	184499	75183	9979	830
36	DEU	1174	598	21543	81700	1059	595	87
	FRA	1218	396	25119	172073	688	90	38
	GBR	1020	740	22814	113310	513	29	22
	JPN	1021	185	17134	98094	4660	586	36
	USA	1410	2598	33831	97257	4299	1497	115
37	DEU	1172	2196	23592	70256	1808	432	71
	FRA	1095	727	23528	190052	1262	420	145
	GBR	681	6761	20635	182870	829	196	109
	JPN	1688	27	24980	211877	9514	2097	139
	USA	1181	2245	34869	225744	5011	2845	223
381	DEU	1340	2069	19369	22617	2547	498	78
	FRA	1090	1144	19636	64056	558	409	194
	GBR	886	2804	18178	53420	529	164	99
	JPN	900	1957	16028	54444	2630	958	74
	USA	1467	2369	30879	74469	5057	2527	187

Table 4-4--continued

Sector	Nation	F^{fs}_{90}	F^{rs}_{90}	G_{90} (\$)	K_{90} (\$)	A^{do}_{90} (mill. \$)	A^{dc}_{90} (mill. \$)	A^{f}_{90} (mill. \$)
382	DEU	1091	5384	21931	39882	14485	531	226
	FRA	1280	2423	22707	58668	4936	307	243
	GBR	947	4606	18813	42560	6973	234	209
	JPN	1519	599	22064	47724	28375	2130	359
	USA	1834	4479	41586	82204	69307	2027	294
383	DEU	1354	3054	26406	44035	27534	879	222
	FRA	1402	1538	24287	59382	15566	166	155
	GBR	1251	4553	26086	42773	17084	171	161
	JPN	1969	363	25295	46852	48519	2643	323
	USA	1816	3089	38727	86905	83919	3183	339
384	DEU	1216	2258	27237	71291	23828	1846	332
	FRA	1037	2728	20438	85241	18402	525	236
	GBR	1177	15024	25887	66543	14469	355	254
	JPN	1601	183	26459	95650	25500	4102	257
	USA	1826	5452	46454	91108	174282	4175	382
385	DEU	943	1728	17942	50013	1734	140	23
	FRA	1970	838	33747	94104	727	71	29
	GBR	1680	888	25340	36547	891	42	20
	JPN	1075	273	19246	79411	5886	648	69
	USA	1793	4643	37567	67948	30766	1981	162
39	DEU	1192	223	15582	39498	148	445	73
	FRA	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	GBR	1206	3014	23822	57100	389	75	47
	JPN	1103	527	14059	27186	1455	453	36
	USA	1725	688	22778	37687	2646	496	39
4+5+6+ 7+8+9	DEU	998	37	16152	215051	3298	18126	4074
	FRA	1007	46	18369	233031	3747	11225	5408
	GBR	723	89	12672	125483	6229	13337	6900
	JPN	982	86	14259	84335	6241	44190	6890
	USA	1099	114	20949	164305	43944	174449	10036

Notes: F^{fs} = TFP (fixed shares). F^{rs} = TFP (revenue shares). G = average real wage in 1985 dollars. K = physical capital stock per worker in 1985 dollars, beginning of year. A^{do} = domestic own-sector R&D capital stock in 1985 dollars, beginning of year. A^{dc} = domestic cross-sector R&D spillovers in 1985 dollars, beginning of year. A^{f} = foreign R&D spillovers in 1985 dollars, beginning of year.

Table 4-5. Summary Statistics: 1990-1978 Ratios

Sector	Nation	F^{fs}_{90}/F^{fs}_{78}	F^{rs}_{90}/F^{rs}_{78}	G_{90}/G_{78}	K_{90}/K_{78}	A^{do}_{90}/A^{do}_{78}	A^{dc}_{90}/A^{dc}_{78}	A^{f}_{90}/A^{f}_{78}
31	DEU	1.10	1.05	1.14	1.16	2.56	1.90	2.22
	FRA	0.98	0.92	1.13	1.45	2.12	2.02	3.44
	GBR	1.22	1.16	1.46	1.56	0.88	1.16	2.37
	JPN	0.90	0.73	1.31	1.84	2.67	3.23	4.08
	USA	1.10	1.04	1.02	1.41	1.64	1.66	4.23
32	DEU	1.23	1.23	1.31	1.36	2.13	1.73	2.27
	FRA	1.22	1.24	1.34	1.77	0.77	2.25	4.02
	GBR	1.13	1.22	1.32	1.67	0.30	0.57	2.08
	JPN	0.99	0.99	1.45	1.83	2.18	2.98	4.12
	USA	1.37	1.40	1.44	1.35	1.39	1.59	3.50
33	DEU	0.95	0.96	0.97	1.09	4.11	1.69	2.17
	FRA	1.06	1.03	1.15	1.76	1.56	2.26	3.94
	GBR	0.85	0.86	0.97	1.08	0.77	2.34	6.62
	JPN	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	USA	1.16	1.16	1.28	1.10	1.12	1.13	3.48
34	DEU	1.08	1.07	1.13	1.28	2.52	2.54	2.90
	FRA	1.02	1.01	1.08	1.64	1.94	3.76	6.18
	GBR	1.13	1.17	1.29	1.60	0.88	1.09	4.20
	JPN	1.35	1.15	1.64	2.01	2.29	4.11	5.00
	USA	0.91	0.90	0.95	1.26	1.37	2.72	6.19
35	DEU	1.02	1.03	1.15	0.97	1.62	2.17	2.92
	FRA	1.21	1.12	1.26	1.35	1.77	2.36	4.46
	GBR	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	JPN	1.28	1.02	1.59	1.72	2.41	3.08	3.95
	USA	1.30	1.24	1.21	1.30	1.60	1.59	4.50
36	DEU	1.19	1.18	1.19	1.20	2.83	1.79	2.15
	FRA	1.24	1.18	1.26	1.73	1.14	0.68	1.14
	GBR	1.11	1.10	1.15	1.59	0.75	0.15	0.45
	JPN	1.44	1.28	1.73	2.13	3.02	2.35	2.71
	USA	1.11	1.13	1.28	1.25	1.44	1.18	3.36
37	DEU	1.37	1.37	1.23	1.00	1.03	1.79	2.56
	FRA	1.44	1.41	1.21	1.61	1.41	1.71	2.56
	GBR	1.98	2.27	1.97	2.06	0.63	0.68	1.36
	JPN	1.28	1.20	1.63	1.22	2.26	1.65	1.87
	USA	0.86	0.88	1.01	1.63	0.93	1.09	2.95
381	DEU	1.07	1.08	1.09	1.20	6.25	2.38	3.40
	FRA	1.03	1.03	1.08	1.64	1.51	3.19	5.21
	GBR	1.14	1.19	1.29	1.58	1.17	0.92	2.23
	JPN	1.49	1.57	1.59	2.23	2.40	6.19	8.82
	USA	1.12	1.14	1.22	1.57	1.28	1.59	4.31

Table 4-5--continued

Sector	Nation	F^{fs}_{90}/F^{fs}_{78}	F^{rs}_{90}/F^{rs}_{78}	G_{90}/G_{78}	K_{90}/K_{78}	A^{do}_{90}/A^{do}_{78}	A^{dc}_{90}/A^{dc}_{78}	A^{f}_{90}/A^{f}_{78}
382	DEU	0.93	0.95	1.00	1.15	2.19	1.98	3.41
	FRA	1.12	1.15	1.11	1.54	1.53	3.16	4.56
	GBR	1.03	1.10	1.19	1.53	1.50	1.06	2.27
	JPN	2.04	1.94	1.88	1.76	3.60	5.77	6.09
	USA	1.11	1.17	1.42	1.89	1.90	1.25	3.99
383	DEU	1.32	1.36	1.51	1.49	1.84	3.03	3.81
	FRA	1.38	1.39	1.48	1.96	1.90	2.40	4.58
	GBR	1.36	1.47	1.73	1.97	1.74	1.11	2.21
	JPN	3.63	3.17	3.94	2.37	3.06	20.97	16.09
	USA	1.43	1.48	1.63	2.03	1.17	2.09	4.84
384	DEU	0.98	1.00	1.27	1.48	2.12	2.99	3.51
	FRA	1.00	1.06	1.02	2.17	1.71	2.50	4.13
	GBR	1.32	1.57	1.41	2.17	1.04	1.24	2.24
	JPN	1.32	1.16	1.83	2.01	2.88	3.75	3.93
	USA	0.97	1.00	1.12	1.40	1.48	1.84	4.74
385	DEU	1.08	1.10	1.14	1.29	1.72	2.08	2.79
	FRA	1.20	1.16	1.19	1.59	1.68	2.50	4.05
	GBR	2.84	2.72	3.28	1.94	0.98	1.32	1.97
	JPN	1.60	1.36	2.52	3.83	3.74	8.36	9.81
	USA	1.11	1.19	1.39	2.10	2.08	3.67	10.29
39	DEU	0.95	0.88	1.09	1.62	6.94	2.43	3.25
	FRA	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	GBR	1.40	1.48	1.68	2.01	0.97	2.66	6.50
	JPN	1.25	1.19	1.37	2.10	2.12	1.91	1.99
	USA	1.37	1.33	1.22	1.37	1.10	1.39	3.88
4+5+6+7+8+9	DEU	1.17	1.11	1.10	1.23	1.80	2.49	3.59
	FRA	1.20	1.14	1.18	1.21	2.00	1.72	3.49
	GBR	1.08	1.08	1.05	0.98	1.85	1.49	3.30
	JPN	1.19	1.08	1.33	1.54	1.84	2.50	4.42
	USA	1.00	1.00	1.03	1.02	4.16	1.68	4.94

Note: See the notes below table 4-4 for definitions of variables.

Table 4-6. Simple Statistics of Logs of Variables

	Number of observations	Mean	Standard deviation	Minimum	Maximum
Log F^{fs}	871	6.98	0.31	5.69	7.83
Log F^{rs}	871	6.50	1.53	2.28	9.66
Log G	871	9.85	0.35	8.47	10.75
Log K	871	11.03	0.63	9.47	12.59
Log A^{do}	871	7.82	1.78	3.06	12.07
Log A^{dc}	871	6.39	1.58	3.34	12.07
Log A^{f}	871	4.61	1.35	1.95	9.21

Note: See the notes below table 4-4 for definitions of variables.

Table 4-7. Simple Correlation Coefficients of Logs of Variables

	Log F^{fs}	Log F^{rs}	Log G	Log K	Log A^{do}	Log A^{dc}	Log A^{f}
Log F^{fs}		-0.1165	0.7583	0.2452	0.4520	0.2729	0.1598
Log F^{rs}	0.0006		0.3094	-0.4549	-0.0011	-0.3983	-0.2806
Log G	0.0001	0.0001		0.4225	0.4559	0.2167	0.2190
Log K	0.0001	0.0001	0.0001		0.2467	0.5082	0.5373
Log A^{do}	0.0001	0.9735	0.0001	0.0001		0.5406	0.4364
Log A^{dc}	0.0001	0.0001	0.0001	0.0001	0.0001		0.8217
Log A^{f}	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	

Note: Entries above the diagonal are Pearson correlation coefficients. Entries below the diagonal are p-values. See the notes below table 4-4 for definitions of variables.

Table 4-7 reports a correlation analysis of the log of variables. The correlation coefficient of 0.8217 between domestic cross-sector spillovers and foreign spillovers confirms our worry about multicollinearity caused by the high correlation between domestic and imported capital flows revealed by table 4-1 and table 4-2.

Results

We investigate simultaneous international and intersectoral R&D spillovers in a standard framework of panel data analysis with country- and sector-specific fixed effects. Since sectoral data are much noisier than aggregate data, we estimate all the regressions in level form.

The Effects of R&D Spillovers on TFP

We first investigate the effects of R&D spillovers on TFP. Table 4-8 reports six regressions using the log of TFP calculated with fixed shares of labor as the dependent variable. The first three regressions include time effects, but the last three do not.

The regressions in table 4-8 show that the effect of the domestic own-sector R&D stock on TFP constructed with fixed shares of labor is insignificant. This counter-intuitive result strengthens our belief that a common labor share for all industries and all countries is unrealistic. A uniform share of labor for all industries and all countries understates the variations in TFP, causing large measurement errors.

The regressions in table 4-8 also show that the domestic cross-sector R&D spillovers and the foreign R&D spillovers have positive and significant effects on TFP when they enter the regression separately. However, when they enter the regression simultaneously, the coefficient of the domestic cross-sector R&D spillovers becomes insignificant, indicating the existence of the multicollinearity problem.

Table 4-9 reports six regressions using log of TFP calculated with revenue shares of labor as the dependent variable. The first three regressions include time effects, but the last three do not.

The regressions in table 4-9 show that the effect of the domestic own-sector R&D stock on TFP constructed with revenue shares of labor is positive and significant. However, the magnitudes of elasticities of TFP with respect to the domestic own-sector R&D stock are far beyond the normal range of 0.06 to 0.1 (Griliches, 1988, p.15).

Moreover, when the domestic cross-sector R&D spillovers and the foreign R&D spillovers enter the regression simultaneously, they have coefficients of gigantic magnitudes but opposing signs. Furthermore, when the domestic cross-sector R&D spillovers and foreign R&D spillovers enter the regression separately, neither of them is significantly positive. All these are indicators of severe measurement errors.

As we discussed in the data section, the excessive variation in revenue shares of labor overstates the volatility of TFP, causing large measurement errors.

The Effects of R&D Spillovers on Wages

We then investigate the effects of R&D spillovers on wages. Table 4-10 reports six regressions with time effects. The first three regressions include the physical capital stock per worker as a control variable, but the last three do not.

Table 4-8. TFP (Fixed Shares) Regression Results

Dependent variable	Log of TFP (fixed shares)					
Regression number	8.1	8.2	8.3	8.4	8.5	8.6
Log A^{do}	-0.007 (0.014)	-0.010 (0.014)	-0.006 (0.014)	0.008 (0.014)	0.016 (0.014)	0.008 (0.014)
Log A^{dc}	0.004 (0.030)	0.049 (0.016)**		-0.028 (0.028)	0.109 (0.015)**	
Log A^{f}	0.056 (0.031)$^{+}$		0.059 (0.017)**	0.132 (0.023)**		0.113 (0.012)**
Time effects	Yes	Yes	Yes	No	No	No
R^2	0.663	0.662	0.663	0.650	0.636	0.650
R^2 adjusted	0.650	0.649	0.651	0.642	0.628	0.642
Standard error	0.181	0.181	0.181	0.183	0.187	0.183
Observations	871	871	871	871	871	871

Notes: A^{do} = domestic own-sector R&D capital stock, A^{dc} = domestic cross-sector R&D spillovers embodied in capital goods, A^{f} = foreign R&D spillovers embodied in capital goods imports. Numbers in parentheses are standard errors. "**" indicates significance at the 1% level, "*" indicates significance at the 5% level, and "+" indicates significance at the 10% level.

Table 4-9. TFP (Revenue Shares) Regression Results

Dependent variable	Log of TFP (revenue shares)					
Regression number	9.1	9.2	9.3	9.4	9.5	9.6
Log A^{do}	0.267 (0.050)**	0.231 (0.050)**	0.211 (0.051)**	0.239 (0.048)**	0.266 (0.049)**	0.219 (0.049)**
Log A^{dc}	-0.764 (0.105)**	-0.229 (0.059)**		-0.654 (0.096)**	-0.147 (0.052)**	
Log A^{f}	0.663 (0.108)**		0.004 (0.062)	0.490 (0.079)**		0.034 (0.043)
Time effects	Yes	Yes	Yes	No	No	No
R^2	0.834	0.826	0.823	0.832	0.824	0.823
R^2 adjusted	0.827	0.820	0.817	0.828	0.820	0.819
Standard error	0.637	0.651	0.656	0.636	0.649	0.652
Observations	871	871	871	871	871	871

Note: See the notes below table 4-8 for definitions of variables.

Table 4-10. Wage Regression Results with Time Effects

Dependent variable	Log of average real wage					
Regression number	10.1	10.2	10.3	10.4	10.5	10.6
Log K	0.221 (0.018)**	0.206 (0.018)**	0.212 (0.018)**			
Log A^{do}	0.043 (0.012)**	0.036 (0.012)**	0.037 (0.012)**	0.030 (0.013)*	0.027 (0.012)*	0.029 (0.012)*
Log A^{dc}	-0.068 (0.025)**	0.023 (0.014)$^+$		-0.010 (0.027)	0.030 (0.015)*	
Log A^f	0.112 (0.026)**		0.053 (0.014)**	0.050 (0.027)$^+$		0.041 (0.015)**
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.825	0.821	0.823	0.794	0.793	0.794
R^2 adjusted	0.818	0.814	0.816	0.786	0.785	0.786
Standard error	0.149	0.151	0.150	0.161	0.162	0.161
Observations	871	871	871	871	871	871

Notes: K = physical capital stock per worker, A^{do} = domestic own-sector R&D capital stock, A^{dc} = domestic cross-sector R&D spillovers embodied in capital goods, A^f = foreign R&D spillovers embodied in capital goods imports. Numbers in parentheses are standard errors. "**" indicates significance at the 1% level, "*" indicates significance at the 5% level, and "+" indicates significance at the 10% level.

Table 4-11. Wage Regression Results without Time Effects

Dependent variable	Log of average real wage					
Regression number	11.1	11.2	11.3	11.4	11.5	11.6
Log K	0.234 (0.017)**	0.251 (0.017)**	0.233 (0.017)**			
Log A^{do}	0.049 (0.011)**	0.056 (0.011)**	0.046 (0.011)**	0.053 (0.012)**	0.063 (0.013)**	0.051 (0.012)**
Log A^{dc}	-0.085 (0.022)**	0.060 (0.013)**		-0.079 (0.025)**	0.104 (0.014)**	
Log A^{f}	0.143 (0.019)**		0.084 (0.010)**	0.177 (0.020)**		0.122 (0.011)**
Time effects	No	No	No	No	No	No
R^2	0.823	0.811	0.820	0.782	0.763	0.779
R^2 adjusted	0.819	0.806	0.816	0.777	0.757	0.774
Standard error	0.149	0.154	0.150	0.165	0.172	0.166
Observations	871	871	871	871	871	871

Note: See the notes below table 4-10 for definitions of variables.

These six regressions show that the positive effect of the domestic own-sector R&D stock on wages is statistically significant and robust, with coefficient estimates lying in a range between 0.03 to 0.04.

They also show that the domestic cross-sector R&D spillovers and the foreign R&D spillovers have positive and significant effects on wages when they enter the regression separately. However, when they enter the regression simultaneously, the coefficient of the domestic cross-sector R&D spillovers changes sign from positive to negative, indicating the existence of multicollinearity between these two variables.[4] In fact, multicollinearity between the domestic cross-sector R&D spillovers and the foreign R&D spillovers is predicted in the correlation analysis of table 4-7. In that table, the correlation coefficient between the domestic cross-sector R&D spillovers and the foreign R&D spillovers is about 0.82.

In addition, the first three regressions show that the physical capital per worker has a positive and significant effect on wages. Furthermore, a comparison of the first three and the last three regressions shows that the inclusion of the physical capital per worker makes the domestic own-sector R&D stock and the foreign R&D spillovers even more statistically significant.

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[4] The multicollinearity problem probably also exists in regressions of Keller (1997), especially when the cross-sector spillovers are constructed using the technology flow matrix of Evenson, Putnam, and Kortum (1991). When he includes foreign cross-sector spillovers and domestic cross-sector spillovers in his regressions, the coefficient of foreign cross-sector spillovers is always negative, but the coefficient of domestic cross-sector spillovers is always positive and more significant than without the presence of foreign cross-sector spillovers. Keller does not show any regression with foreign cross-sector spillovers but without domestic cross-sector spillovers. If such regressions

Table 4-11 reports six regressions without time effects. The first three regressions include the physical capital stock per worker as a control variable, but the last three do not.

Table 4-11 shows that the physical capital per worker and the domestic own-sector R&D stock have statistically significant and robust effects on wages. Table 4-11 also shows that without time effects, the symptoms of multicollinearity between the domestic cross-sector R&D spillovers and the foreign R&D spillovers are still there. In fact, they are even more obvious in table 4-11 than in table 4-10.

A comparison of table 4-11 against table 4-10 shows that the exclusion of time effects makes all other regressors statistically more significant. This is so because what time effects capture is more of a positive secular trend than of cyclical fluctuations.

Summary

In this chapter, we extend our empirical investigation of international R&D spillovers down to the sectoral level. We find that, in addition to domestic own-sector R&D stock, domestic cross-sector R&D spillovers and foreign R&D spillovers embodied in flows of capital goods have positive effects on wages. Experiments with control variables such as physical capital per worker and time effects show that the positive correlation between wages and spillovers is robust.

However, domestic cross-sector R&D spillovers and foreign R&D spillovers are so highly correlated to each other that their individual effects cannot be separated. We

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produce a positive coefficient for foreign cross-sector spillovers, then the suspicion of trace the source of multicollinearity to the highly correlated domestic and imported capital formation tables of the OECD. How to isolate these two spillovers empirically is an important topic for future research.

We also find measurement error problems in TFP data constructed by the OECD using fixed shares of labor and alternative TFP data constructed using revenue shares of labor. How to measure productivity at the sectoral level accurately is another important topic for future research.

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multicollinearity will be confirmed.

CHAPTER 5
CONCLUSIONS

Existing R&D-based models of economic growth have underscored the fact that the engine of economic growth is technological change, and that the fuel of technological change is human capital. However, they have overlooked the fact that the distribution of human capital is far more skewed than that of labor. This seemingly innocuous neglect has rendered these models incapable of explaining recent trends in developed countries: increasing R&D employment, nearly constant TFP growth, and widening wage differentials.

In chapter 2, we recast the endogenous technological change model of Romer (1990) in a heterogeneous society where human capital is distributed unequally among the population and is allocated jointly with labor between R&D and manufacturing. Our model introduces distribution effects in addition to scale effects. Because calibration based on observed income differentials and the manufacturing share of employment shows that the inequality in human capital endowment is sizable, the distribution effect on growth is much weaker than the scale effect.

With distribution effects, our new heterogeneous vintage of R&D-based models of economic growth is consistent with most of the stylized facts, but the relevant unit of observation is neither any sovereign nation nor the whole world, but rather an integrated subworld. When the integrated subworld expands to incorporate developing economies, it absorbs human capital and labor in proportions more uneven than its own and thus becomes more heterogeneous. As a result, wage differentials increase, workers switch from manufacturing to R&D at the margin, but the growth rate may rise only moderately.

Our heterogeneous growth model indicates that human capital is the fundamental source of the wealth of nations. In the long run, therefore, convergence/divergence in per capita human capital leads to convergence/divergence in per capita income.

In chapter 3, we investigate international R&D spillovers through trade and FDI among industrialized countries. Our results show that capital goods trade is a good proxy for channels of international R&D spillovers. We estimate that more than one third of the total benefits of R&D investment in a G7 country accrue to its trade partners within the OECD, which is significantly higher than those reported in the literature. Although no correlation is found between TFP and a measure of foreign R&D spillovers embodied in FDI, a significant correlation is found between TFP and the intensity of FDI. In addition, we find that domestic R&D activities enhance the ability of relatively large countries (G7 except the United States) to absorb foreign technology.

Our estimates of the effects of R&D spillovers through capital goods trade are robust and are consistent with results from single-country, firm- and industry-level studies. Our estimates of the effects of R&D spillovers through FDI should be interpreted with caution, however, because of the poor quality of FDI data. Further research explorations with better measure of R&D activities of multinational corporations will be useful. The importance of absorptive capacity in international R&D transmission also deserves more attention.

In chapter 4, we extend our empirical investigation of international R&D spillovers down to the sectoral level. We find that, in addition to domestic own-sector R&D stock, domestic cross-sector R&D spillovers and foreign R&D spillovers embodied in flows of capital goods have positive effects on wages. Experiments with control variables such as physical capital per worker and time effects show that the positive correlation between wages and spillovers is robust.

However, domestic cross-sector R&D spillovers and foreign R&D spillovers are so highly correlated to each other that their individual effects cannot be separated. We trace the source of multicollinearity to the highly correlated domestic and imported capital formation tables in the OECD input-output data. How to isolate these two spillovers empirically is an important topic for future research.

We also find measurement error problems in TFP data constructed by the OECD using fixed shares of labor and alternative TFP data constructed using revenue shares of labor. How to measure productivity accurately at the sectoral level is another important topic for future research.

APPENDIX A
DERIVATION AND CALIBRATION FOR ENDOGENOUS TECHNOLOGICAL CHANGE IN A HETEROGENEOUS SOCIETY

The Balanced Growth Path

The maximization of equation (4) in chapter 2 of this dissertation yields conditional aggregate demand functions

$$p(i) = (1-\alpha)L_Y^{\alpha}x(i)^{-\alpha}, \forall i, \tag{A1}$$

$$w_L = \frac{\alpha Y}{L_Y}. \tag{A2}$$

Substituting (A1) into (5) and maximizing, we get monopoly price, quantity, and revenue minus variable cost

$$p(i) = \bar{p} \equiv \frac{r}{1-\alpha}, \forall i, \tag{A3}$$

$$x(i) = \bar{x} \equiv \left(\frac{1-\alpha}{\bar{p}}\right)^{\frac{1}{\alpha}} L_Y, \forall i, \tag{A4}$$

$$\pi(i) = \bar{\pi} \equiv \alpha\bar{p}\bar{x}, \forall i. \tag{A5}$$

Hence, capital accumulation is related to knowledge accumulation as

$$K = \int_0^A x(i)di = \bar{x}A. \tag{A6}$$

Aggregate goods output (3) can then be rewritten as

$$Y = L_Y^{\alpha}\bar{x}^{1-\alpha} A = \left(AL_Y\right)^{\alpha} K^{1-\alpha}. \tag{A7}$$

Since the R&D sector is competitive and employs only one rivalrous input--human capital, all receipts from the sales of new designs are paid to inventors as wages:

$$P_A \delta A H_A = w_H H_A. \tag{A8}$$

Therefore, the wage rate of human capital is

$$w_H = P_A \delta A, \tag{A9}$$

and the inventor wage that individual z earns if she works in the R&D sector is

$$w_H h(z) = \frac{P_A \delta A \mu H}{L}\left(\frac{z}{L}\right)^{\mu-1}. \tag{A10}$$

The equilibrium condition of the joint market of labor and human capital requires that individual L_Y, the marginal inventor, earn the same wage no matter which occupation she choose:

$$w_L = \frac{\alpha Y}{L_Y} = w_H h\left(L_Y\right) = \frac{P_A \delta A \mu H}{L}\left(\frac{L_Y}{L}\right)^{\mu-1}. \tag{A11}$$

Unlike the Romer model in which no one has a preference for any particular occupation, our model indicates that those more talented than L_Y become inventors because they can earn an inventor wage higher than the laborer wage, but those less talented than L_Y never become inventors because they would earn an inventor wage lower than the laborer wage if they did. Hence, who works in an assembly line and who works in an R&D lab are determined by human capital endowment, and so is how much one earns:

$$w(z) = \begin{cases} w_L = w_H h\left(L_Y\right) & z \in \left[0, L_Y\right] \\ w_H h(z) & z \in \left[L_Y, L\right] \end{cases}. \tag{A12}$$

Note that aggregate human capital devoted to invention is

$$H_A = \int_{L_Y}^{L} h(z)dz = H\left[1-\left(\frac{L_Y}{L}\right)^{\mu}\right], \tag{A13}$$

which implies an important relationship between the share of human capital wasted in manufacturing and the share of labor used in manufacturing:

$$\frac{H_Y}{H} = \left(\frac{L_Y}{L}\right)^{\mu}. \tag{A14}$$

Solving (A11) for the price of new designs and substituting in (A7) and (A14), we get

$$P_A = \frac{\alpha L_Y^{\alpha} \bar{x}^{1-\alpha}}{\mu \delta H_Y}. \tag{A15}$$

The equilibrium price of new designs, the profit stream, and the rate of return are connected by the no-arbitrage condition:

$$r = \frac{\bar{\pi}}{P_A} + \frac{\dot{P}_A}{P_A}. \tag{A16}$$

Since r is constant along the balanced growth path, so is $\bar{p}$ from (A3). And since L and H are constant, L_Y and H_Y are also constant along the balanced growth path, so are $\bar{x}$ and $\bar{\pi}$ from (A4) and (A5). Therefore, P_A is constant along the balanced growth path from (A15). After (A5) and (A15) are substituted in, (A16) is simplified to

$$r = \frac{\mu \delta H_Y \bar{p}}{L_Y^{\alpha} \bar{x}^{-\alpha}}. \tag{A17}$$

Using (A4), we can further simplify (A17) to

$$r = \mu(1-\alpha)\delta H_Y. \tag{A18}$$

The maximization of (8) subject to (9) yields the conventional intertemporal optimality condition:

$$g = \frac{\dot{c}}{c} = \frac{r-\rho}{\sigma} = \frac{\dot{A}}{A}. \tag{A19}$$

Substituting (6) and (A18) into (A19), we find

$$\delta H_Y = \frac{\sigma\delta H + \rho}{\mu(1-\alpha)+\sigma}. \tag{A20}$$

Substituting (A20) into (A18), the equilibrium rate of return is

$$r = \frac{\mu(1-\alpha)(\sigma\delta H + \rho)}{\mu(1-\alpha)+\sigma}. \tag{A21}$$

Substituting (A21) into (A19), the balanced growth rate is

$$g = \frac{\mu(1-\alpha)\delta H - \rho}{\mu(1-\alpha)+\sigma}. \tag{A22}$$

Rearranging (A20), the equilibrium share of the human capital wasted in manufacturing is

$$\frac{H_Y}{H} = \frac{\sigma + \dfrac{\rho}{\delta H}}{\mu(1-\alpha)+\sigma}. \tag{A23}$$

The equilibrium share of the population engaged in manufacturing can then be obtained from (A14) as

$$\frac{L_Y}{L} = \left[\frac{\sigma + \dfrac{\rho}{\delta H}}{\mu(1-\alpha)+\sigma}\right]^{\frac{1}{\mu}}. \tag{A24}$$

The equilibrium ratio of the maximum wage to the minimum wage can be derived from (1) and (A24) as

$$\frac{w(L)}{w(L_Y)} = \frac{w_H h(L)}{w_L} = \frac{w_H h(L)}{w_H h(L_Y)} = \left(\frac{L_Y}{L}\right)^{1-\mu} = \left[\frac{\sigma + \dfrac{\rho}{\delta H}}{\mu(1-\alpha)+\sigma}\right]^{\frac{1-\mu}{\mu}}. \tag{A25}$$

Combining (A32) and (A35), we get the equilibrium ratio of the aggregate wage income of inventors to that of laborers

$$\frac{w_H H_A}{w_L L_Y} = \frac{(1-\alpha)g}{r} = \frac{\mu(1-\alpha)\delta H - \rho}{\mu(\sigma\delta H + \rho)}. \tag{A26}$$

The equilibrium ratio of the average inventor wage to the (average) laborer wage is then

$$\frac{w_H H_A}{w_L L_A} = \left(\frac{w_H H_A}{w_L L_Y}\right)\left[\left(\frac{L_Y}{L}\right)^{-1} - 1\right]^{-1} =$$

$$\frac{\mu(1-\alpha)\delta H - \rho}{\mu(\sigma\delta H + \rho)}\left\{\left[\frac{\sigma + \dfrac{\rho}{\delta H}}{\mu(1-\alpha)+\sigma}\right]^{-\frac{1}{\mu}} - 1\right\}^{-1}. \tag{A27}$$

The National Income Accounts

Integration of equation (9) in chapter 2 across all individuals yields the national income accounts

$$\dot{K} + P_A\dot{A} + C = rK + rP_A A + w_L L_Y + w_H H_A \tag{A28}$$

where $\dot{K}, P_A\dot{A}, C, rK, rP_A A$, $w_L L_Y$ and $w_H H_A$ are aggregates of investment in capital, investment in designs, consumption, returns on capital, returns on designs, compensation of labor from manufacturing, and compensation of human capital from R&D. Note that in (A28), aggregate wage income is decomposed as

$$W = \int_0^L w(z)dz = \int_0^{L_Y} w_L dz + \int_{L_Y}^L w_H h(z)dz = w_L L_Y + w_H H_A. \tag{A29}$$

Canceling identical terms $P_A\dot{A} = w_H H_A$ from both sides of (A28), the aggregate goods output, or the physical national income accounts, is

$$Y = \dot{K} + C = rK + rP_A A + w_L L_Y . \tag{A30}$$

According to (4), the zero-profit condition of the final goods sector is

$$Y - w_L L_Y - \overline{p}\overline{x}A = 0 . \tag{A31}$$

Rearranging (A2) and we get

$$w_L L_Y = \alpha Y . \tag{A32}$$

Substituting (A3), (A6), and (A32) into (A31) and rearranging, we get

$$rK = (1-\alpha)^2 Y . \tag{A33}$$

Substituting (A32) and (A33) into (A30) and rearranging, we get

$$rP_A A = \alpha(1-\alpha)Y . \tag{A34}$$

All other terms in the national income accounts can then be expressed in terms of α, g, r, and Y:

$$P_A \dot{A} = w_H H_A = \frac{\alpha(1-\alpha)gY}{r} , \tag{A35}$$

$$\dot{K} = \frac{(1-\alpha)^2 gY}{r} , \tag{A36}$$

$$C = \frac{\left[r-(1-\alpha)^2 g\right]Y}{r} , \tag{A37}$$

$$W = w_L L_Y + w_H H_A = \frac{\alpha\left[r+(1-\alpha)g\right]Y}{r} .[1] \tag{A38}$$

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[1] Components of the individual dynamic budget constraint (9), $\dot{k}(z), k(z), \dot{a}(z), a(z)$, and $c(z)$, can be expressed respectively as the products of corresponding aggregates and the individual share *w(z)/W* which is constant along the balanced growth path.

Apparently, all components of the national income accounts are proportional to Y and thus all grow at the same exponential rate g along the balanced growth path. It can be shown that

$$Y = \mu^{\frac{\alpha-1}{\alpha}} (1-\alpha)^{\frac{1-\alpha}{\alpha}} (\delta H)^{\frac{\alpha-1}{\alpha}} \left[\frac{\sigma + \frac{\rho}{\delta H}}{\mu(1-\alpha)+\sigma} \right]^{\frac{\alpha-1}{\alpha}+\frac{1}{\mu}} LA. \tag{A39}$$

However, the shares of the national income accounts can be expressed in terms of α, g, and r only, and thus are constant along the balanced growth path. Hence, the knowledge investment share of aggregate expenditure (the inventors' wage share of national income) is

$$\frac{P_A \dot{A}}{Y + P_A \dot{A}} = \frac{w_H H_A}{Y + P_A \dot{A}} = \frac{\alpha(1-\alpha)g}{r + \alpha(1-\alpha)g}. \tag{A40}$$

The physical investment share of aggregate expenditure is

$$\frac{\dot{K}}{Y + P_A \dot{A}} = \frac{(1-\alpha)^2 g}{r + \alpha(1-\alpha)g}. \tag{A41}$$

The consumption share of aggregate expenditure is

$$\frac{C}{Y + P_A \dot{A}} = \frac{r - (1-\alpha)^2 g}{r + \alpha(1-\alpha)g}. \tag{A42}$$

The laborers' wage share of national income is

$$\frac{w_L L_Y}{Y + P_A \dot{A}} = \frac{\alpha r}{r + \alpha(1-\alpha)g}. \tag{A43}$$

The physical capital share of national income is

$$\frac{rK}{Y + P_A \dot{A}} = \frac{(1-\alpha)^2 r}{r + \alpha(1-\alpha)g}. \tag{A44}$$

Finally, the knowledge capital share of national income is

$$\frac{rP_A A}{Y+P_A \dot{A}}=\frac{\alpha(1-\alpha)r}{r+\alpha(1-\alpha)g}. \tag{A45}$$

Since more or less accurate measures of α, g, and r are available in the real world, calibration is carried out in table A-1. Barro and Sala-i-Martin (1995, p.124) give $g = 0.02$, $r = 0.06$. But we also want to try $g = 0.03$ and $r = 0.09$, and we assume that $\alpha = 2/3$.[2]

Table A-1. Calibration of the Shares of the National Income Accounts

g	0.02	0.02	0.03	0.03
r	0.06	0.09	0.06	0.09
$P_A\dot{A}/(Y+P_A\dot{A})$	6.90%	4.71%	10.00%	6.90%
$\dot{K}/(Y+P_A\dot{A})$	3.45%	2.35%	5.00%	3.45%
$C/(Y+P_A\dot{A})$	89.65%	92.94%	85.00%	89.65%
$w_L L_Y/(Y+P_A\dot{A})$	62.07%	63.53%	60.00%	62.07%
$rK/(Y+P_A\dot{A})$	10.34%	10.59%	10.00%	10.34%
$rP_A A/(Y+P_A\dot{A})$	20.69%	21.18%	20.00%	20.69%

Row 3 of table A-1 shows that the output of the knowledge-producing sector usually comprises no more than one tenth of the aggregate output. Rows 3 and 4 show that investment in new knowledge and investment in new capital account for two thirds and one third of total investment respectively, and the summation of rows 3 and 4 gives the range of our hypothetical society's investment rate. Note that this range is consistent with the real world statistics. Note also that if investment in new knowledge, $P_A\dot{A} = w_H H_A$, is partially or totally excluded from both sides of the national income accounts for some reason, a false impression of underinvestment will be caused. Rows 3 and 6 show that the knowledge-producing sector usually comprises no more than one seventh of the economy in terms of employees' compensation.

How Heterogeneous a Society Can Be?

In chapter 2, if we divide the log of equation (13) by the log of equation (12) and rearrange, the distribution parameter can be solved as

$$\mu = 1 - \frac{\ln[w(L)/w(L_Y)]}{\ln(L_Y/L)}. \tag{A46}$$

Hence, if we can get measures of the wage limits ratio, $w(L)/w(L_Y)$, and the manufacturing share of employment, L_Y/L, from the real world, then the magnitude of the distribution parameter can be estimated indirectly.

However, the calibration of the real world is an intellectually challenging enterprise. First, what is the knowledge-producing sector's share of employment in the integrated subworld? Unfortunately, no one has ever worked out any statistics about this integrated subworld, and even if such statistics were available, different definitions might result in numbers of different orders of magnitude. Take the United States as an example. On one

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[2] See footnote 7 in chapter 2 for a discussion about the difference between our α, the

hand, the pioneering work of Machlup (1962) on "knowledge industries" gives such an unusually broad definition of knowledge and knowledge-producing activities that he concludes that the ratio of workers in the labor force who were engaged in knowledge-producing activities to America's total civilian labor force was 31.6% in 1959. More recently, Reich (1991, p.179) estimates that symbolic analysts comprised no more than 8% of the American labor force around 1950 compared with no more than 20% around 1990. On the other hand, Jones (1995a) cites official statistics that the ratio of the full-time-equivalent number of scientists and engineers devoted to R&D to the entire working population in the United States has grown from about 0.25% in 1950 to about 0.80% in 1988.

The problems with Machlup and Reich's numbers are that their calculations are based on definitions that are too broad,[3] and that they are not calculated on a full-time-equivalent basis. This leaves us with only the official statistics of formal R&D employment shares for a dozen or so developed countries. These statistics may be biased downward because their definitions are so narrow as to cover only a fraction of all knowledge-producing activities. However, they may equally likely be biased upward because they are collected in countries where knowledge-producing sector's share of employment should be several times as large as in the integrated subworld as a whole. Therefore, our best guess would be that these two biases approximately cancel each other

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labor share of goods output, and the conventional labor share of national income.

[3] Machlup's knowledge producing sectors include Education, Research and Development, the Media of Communication, Information Machines, and Information Service. Reich (1991, pp. 177-178) has a long list of symbolic analysts consisting of "research scientists,

so that in our contemporary integrated subworld, the knowledge-producing sector's share of employment lies in a range between 0.5% and 2%, about the same magnitude as the recent employment share of America's formal R&D.

As a matter of fact, our guess has a theoretical justification. Rows 3 and 6 of table A-1 shows that employees of the knowledge-producing sector usually receive about one tenth of the aggregate wage income. This implies that the employment share of the R&D sector would be around 10% only if individuals were more or less homogeneous ($\mu \approx 1$). Therefore, in addition to two values of the manufacturing share of work force, 98% and 99.5%, corresponding to two values of the R&D share of work force, 2% and 0.5%, respectively, we will try a 90% manufacturing share of work force, corresponding to a 10% R&D share of work force, to see if the resulting estimates of μ are close to one or not. As will be shown below, the estimate of μ thus obtained exceeds one by a large amount, implying that the employment share of the R&D sector is much less than 10%.

The measurement of the wage limits ratio seems to be an easier job. In the first half of 1990s, Jerome Lemelson, America's (and presumably, the world's) most productive and thus best paid inventor, collected about half a billion dollars from his patents (Rosen 1995).[4] Of course, this astronomical sum is in fact the fruits of his hard work over a period much longer than five years. Hence, if we assume that this sum of half billion dollars is his entire lifetime income, an average over half a century yields an

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···, public relations executives, investment bankers, lawyers, real estate developers, ···, musicians, television and film producers, and even university professors."

[4] Lemelson is chosen not only for his fecundity and contemporaneity but also for his single-handedliness, which makes him a true independent inventor and enables us to measure correctly how productive an inventor can be.

annual earning of \$10,000,000. During the same period, about 90% of American full-time year-round workers had an annual earning of more than \$10,000. If we assume a minimum wage income of \$10,000 per year for our laborers and marginal inventor, 1,000 will be our estimate for $w(L)/w(L_Y)$. Some might argue that the bulk of Mr. Lemelson's lifetime income is still on the way and thus 1,000 is biased downward. In contrast, others might argue that the greater part of his fortune is the result of sheer luck instead of unusual ability and thus 1,000 is biased upward. Being unable to judge the relative strength of these two arguments, we will try 200 and 5,000 as well.

Table A-2. Calibration of a Heterogeneous Society

L_Y/L	90%	90%	90%	98%	98%	98%	99.5%	99.5%	99.5%
$w(L)/w(L_Y)$	200	1000	5000	200	1000	5000	200	1000	5000
μ	51.29	66.56	81.84	263.3	342.9	422.6	1058	1379	1700
H_Y/H	0.45%	0.09%	0.02%	0.49%	0.10%	0.02%	0.50%	0.10%	0.02%

Row 3 of table A-2 shows that the distribution of human capital endowment is so highly skewed that the most talented may be hundreds of times more productive in knowledge production than an individual of the average human capital endowment, not to mention the median individual and those below. Rows 1 and 4 show that human capital is such a valuable resource compared with labor that societies tend to utilize almost their entire human capital endowment in knowledge production and are willing to bear the cost of wasting a considerable portion of their labor endowment if necessary. Rows 1, 3, and 4 indicate that the more heterogeneous a society is, the less labor is allocated to and thus wasted in the knowledge-producing sector, that is, the more efficient it is in human resource allocation. Also, row 3 of table A-2 shows that the distribution parameter is very sensitive to the employment share of the knowledge-producing sector while row 2 shows that the wage limits ratio has only a mild impact on the distribution parameter. Hence, the measurement of the employment share of the knowledge-producing sector is essential to the estimation of the distribution parameter.

APPENDIX B
DATA DESCRIPTION FOR INTERNATIONAL R&D SPILLOVERS

Our sample is a panel of 21 OECD countries over the 1984-1990 period. The 21 countries are the United States (USA), Japan (JPN), western Germany (DEU), France (FRA), Italy (ITA), Great Britain (GBR), Canada (CAN), Australia (AUS), Austria (AUT), Belgium (BEL), Denmark (DNK), Finland (FIN), Greece (GRC), Ireland (IRL), the Netherlands (NLD), Norway (NOR), New Zealand (NZL), Portugal (PRT), Spain (ESP), Sweden (SWE), and Switzerland (CHE).

Part of the data is from Coe and Helpman (1995). TFP data are from their table A.1, which are indices with 1985 = 1. TFP is defined as $Y/L^{(1-\beta)}K^{\beta}$, where Y is value-added in the business sector, K and L are the capital stock and labor employment in the business sector respectively. The *values* of domestic R&D capital stocks are calculated based on CH's table A.3 (domestic R&D capital stock indices with 1985 = 1) and table A.7 (the values of domestic R&D capital stocks in 1990). The unit of domestic R&D capital stocks is billion U.S. dollars, based on PPP's and in constant 1985 prices. For details of the construction of TFP and domestic R&D capital stocks, see CH's Appendix A.

Our bilateral capital goods trade data are from the OECD's Foreign Trade by Commodities. We use imports of machinery and transport equipment (SITC 7) as a proxy for imports of capital goods. We use data reported by importing countries that are almost the same as data reported by exporting countries.

Our bilateral FDI data are from the OECD's International Direct Investment Statistics Yearbook. FDI data are reported as inward flows and inward stocks by destination countries and as outward flows and outward stocks by origin countries. Unfortunately, there are a large number of missing values in all four sets of data. To make things even worse, there are discrepancies, some of them significant ones, between flow data and stock data, and between inward data and outward data.

Using inward flows and outward flows, we are able to estimate some missing values for inward stocks and outward stocks respectively. Still, about a dozen countries have to be dropped from the sample because of their remaining unfilled missing values. Fortunately, those dropouts are relatively insignificant in all four measures of FDI. The 13 countries for which we manage to have complete inward and outward FDI stock data are: Australia, Austria, Canada, France, western Germany, Italy, Japan, the Netherlands, Norway, Sweden, Switzerland, Great Britain, and the United States. Finally, since we are unable to judge the relative reliability of inward stocks and outward stocks, we are forced to take the average of these two.

APPENDIX C
DATA DESCRIPTION FOR INTERNATIONAL AND INTERSECTORAL R&D SPILLOVERS

The Source of Data

A consistent system of refined data is essential to our empirical investigation of R&D spillovers. They are average real wage data, physical capital stock per worker data, TFP data, R&D stock data, and R&D spillovers data (constructed from R&D stock data and normalized bilateral trade flows of capital goods data). Since none of these data exists for an adequate sample of countries at a reasonably detailed level, we had to construct our own variables out of existing data.

The major, if not the only, source of usable data is the OECD publication, and we have collected all the sectoral data available at the OECD. These include (1) the International Sectoral Database (ISDB), (2) the Structural Analysis Database (STAN), (3) the OECD Input-Output Database (I/O), (4) the Bilateral Trade Database (BTD), (5) the Analytical Business Enterprise Research and Development Database (ANBERD) (supplemented by unpublished 1963-1972 data).

Most of these databases cover about a dozen OECD countries at the 4-digit ISIC level. But a close inspection reveals the existence of large number of missing values and discrepancies, especially in the case of 4-digit ISIC industries, service sectors, and small countries. In addition, the documentation of these databases shows that with few exceptions the original data are collected at the 2-digit level, and data for 3- and 4-digit industries are usually estimates based on the data of 2-digit industries under restrictive assumptions. Hence, there is a trade-off between the completeness and reliability of our analysis.

After careful consideration, we choose a sample of five major OECD countries and fourteen industries The five countries are Germany (DEU), France (FRA), Great Britain (GBR), Japan (JPN), and the United States (USA). The fourteen industries are Food, Beverages & Tobacco (ISIC 31), Textiles, Apparel & Leather (ISIC 32), Wood Products & Furniture (ISIC 33), Paper, Paper Products & Printing (ISIC 34), Chemical Products (ISIC 35), Non-Metallic Mineral Products (ISIC 36), Basic Metal Industries (ISIC 37), Metal Products (ISIC 381), Non-Electrical Machinery (ISIC 382), Electrical Machinery (ISIC 383), Transport Equipment (ISIC 384), Professional Goods (ISIC 385), Other Manufacturing (ISIC 39), Total Services (ISIC 4+5+6+7+8+9).

Note that data are missing for Wood Products & Furniture (ISIC 33) in Japan, Chemical Products (ISIC 35) in Great Britain, and Other Manufacturing (ISIC 39) in France. Therefore, we actually have data for 67 cross-sectional units over 13 time periods, or a total of 871 observations.

The Construction of Variables

Total Factor Productivity

At the 2- and 3-digit ISIC level, the OECD ISDB database provides TFP *index* data as well as GDP, employment, and capital stock data used in the construction of TFP data. However, for 3-digit ISIC industries, TFP index data are missing for Great Britain and Japan because GDP and employment data for these countries are missing. In addition, the TFP index is not available for total services. Moreover, since we introduce four country dummies and thirteen sector dummies instead of 66 country-sector dummies so as to separate country effects and sector effects, we have to use TFP level data instead of TFP index data. Hence, our first TFP data set is constructed by replacing the missing values in GDP and employment with data from STAN, aggregating GDP, employment, and Capital stock across all service sectors, and calculating TFP levels following the same methodology as ISDB.

Note that there are inconsistencies between ISDB and STAN in data used in the construction of the TFP for the United States and France. Moreover, the TFP level data are constructed under the simplistic assumption that labor share is constant (0.7) across all countries and all industries.

Since fixed shares of labor are apparently unrealistic, an alternative TFP data set is constructed using country- and sector-specific revenue shares of labor which are calculated as the ratio of labor compensation to value added.

Wages and Capital Stock per Worker

The labor compensation data are in national currency at current prices in ISDB. They are deflated by each country's implicit GDP deflator, and converted into 1985 U.S. dollars using PPPs. The average real wage is then calculated as the ratio of real labor compensation to number engaged in ISDB.

The physical capital stock data are in 1985 U.S. dollars in ISDB. The capital stock per worker is calculated as the ratio of physical capital stock to number engaged.

R&D Stock

We construct R&D stock data from R&D flow data using the perpetual inventory model. R&D flow data of 15 countries for the 1973-1993 period at the 4-digit ISIC level are available in OECD ANBERD database (the latest version). Unpublished R&D data for the 1963-1972 period are also available but are in a much worse shape, with numerous missing values and inconsistencies.

We first match the pre-1973 R&D flow data with the 1973-1990 data, interpolate the series to eliminate missing values, deflate them with implicit GDP deflators, and convert them into 1985 dollars using PPPs. Then we calculate the growth rate over the 1967-1990 period, assume a depreciation rate of 15% per year, and use the perpetual inventory model to construct the R&D stocks.

R&D Spillovers

Cross-country, cross-sector bilateral trade flow data are five-way panel data with the first subscript indicating the exporting country, the second indicating the importing country, the third indicating the exporting industry, the fourth indicating the importing industry, and the fifth indicating the year.

Since flows of goods across every international border are closely monitored by governments on both sides, international trade data are usually available in a double-reporting fashion: flows between any pair of countries are reported by both the origin country and the destination country. Hence, information about the exporting country and the importing country is usually well documented for all open transactions.

However, customs officers never pay any attention to the exporting and importing industries. Of course, exports and imports are usually classified according to some trade classification system, for example, the Standard International Trade Classification (SITC) system. Therefore, information about the exporting industry can be derived using some concordance scheme between the trade classification system and the industry classification system. Still, information about the importing industry is completely missing in trade data.

The only way to construct the cross-country, cross-sector bilateral trade flows of capital goods is to combine the domestic capital flow matrices and the imported capital flow matrices of the OECD Input-Output Database, which records cross-sector capital flows, with the OECD Bilateral Trade Database, which records within-sector cross-country trade flows.

Since input-output data are irregularly spaced time series with years covered varying across countries between 1968 and 1990, interpolation is performed to produce balanced time series for the period of 1978-1990. Before interpolation, the domestic capital flow matrices and the imported capital flow matrices are converted into current dollars using PPPs.

The Bilateral Trade Database includes both imports data reported by the destination country and exports data reported by the origin country, and these two are usually very close to each other. Because of the existence of tariff, the destination country's incentive to monitor imports is stronger than the origin country's incentive to monitor exports. Therefore, we choose the potentially more reliable imports data.

We then combine the input-output data with within-sector import shares obtained from the Bilateral Trade Database to construct the cross-country, cross-sector bilateral trade flows of capital goods. Normalization is carried out by dividing the cross-country, cross-sector bilateral trade flows of capital goods by value added (in current dollars) of the spillover-sending country-sector unit. R&D spillovers are constructed by combining the domestic own-sector R&D stock data with the normalized cross-country, cross-sector bilateral trade flows of capital goods.

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I certify that I have read this study and that in my opinion it conforms to acceptable standards of scholarly presentation and is fully adequate, in scope and quality, as a dissertation for the degree of Doctor of Philosophy.

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